Modeling Building Thermal Response to HVAC Zoning

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Abstract. HVAC systems account for 38% of building energy usage. Studies have indicated at least 5-15% waste due to unoccupied spaces being conditioned. Our goal is to minimize this waste by retrofitting HVAC systems to enable *room-level zoning* where each room is conditioned individually based on its occupancy. This will allow only occupied rooms to be conditioned while saving the energy used to condition unoccupied rooms. In order to achieve this goal, the effect of opening or closing air vent registers on room temperatures has to be predicted. Making such a prediction is complicated by the fact that weather has a larger effect on room temperatures than the settings of air vent registers, making it hard to isolate the influence of the HVAC system. We present a technique for dynamically estimating the heat load due to weather on room temperatures and subtracting it out in order to predict the effect of the HVAC system more directly.

Keywords: Building energy; energy; environment; sensing

1 Introduction

Buildings account for 75% [1] of the electricity and 43% of the greenhouse gas emissions in the United States [2] and the Heating, Ventilation, and Cooling (HVAC) system is the single largest energy consumer in residential buildings, accounting for 43% of the residential energy consumption in the US [3], and over 60% in Canada [4] and the UK [5], which have colder climates. This accounts for 38% of all the building energy used in the United States and over 15% of the total energy used in the U.S., making HVAC systems one of the nation's largest energy consumers. Studies have indicated that at least 5-15% of this waste is due to the course-grained, manual configuration of thermostats by users, whereby spaces are heated or cooled even if not needed by the occupants. Much of this wasted energy is used to heat or cool unoccupied spaces during long periods when people use only a small fraction of a house, such as when they work in an office or sleep in a bedroom. Our vision is to minimize this energy wastage through room-level zoning, where each room is conditioned individually based on its occupancy. This would allow most, if not all, of the energy used by the HVAC system to be focused on maintaining occupied rooms at a comfortable temperature without wasting any energy conditioning unoccupied rooms. Many homes in the United States have centralized HVAC systems that have a single compressor or furnace. Such systems have to be configured for zoning during installation if homeowners want to minimize energy wastage. Most, if not all, zoned HVAC systems are implemented in multi-story houses where each floor is configured to be a separate zone. Due to the room usage generally being separated by floor, so that the bedrooms are on the upper floor and the living spaces on the lower floor, a coarse-grained zoning schedule can be manually configured for such a system allowing energy savings. For example, the system can be configured to condition the upper floor only during the night, when the bedrooms are in use, and the lower floor only during the day, when the living spaces are most likely to be used. Such a scheme cannot be used in a single-story house because the night and day living spaces are adjacent to each other. Also, the fact that rooms on a single floor are not as thermally isolated as rooms on separate floors reduces the energy savings that can be achieved through coarse-grained zoning within a floor.

Our goal is to implement a system that can retrofit the centralized HVAC systems that are in most homes in the United States so that air vents can be controlled individually and room-level zoning can be achieved. Such a system would require an automated controller that decided which rooms have to be conditioned and dynamically alters the zones based on occupancy and room temperature by opening and closing air-vent registers in rooms. In order for such a controller to be efficiently implemented, the affect of opening or closing registers on the temperatures in the room have to be predictable. Thus, in this paper we present and evaluate techniques to learn and predict the effect of opening or closing each vent register, in a set of R air vent registers, on the temperature at each sensor, in a set of T temperature sensors placed within a house.

The main challenge to modeling the thermal characteristics of a house is the effect of weather on the indoor temperature. For instance, wind, solar gain, and outdoor temperature have a greater influence on indoor temperature than any individual air vent register. It is difficult to build a model that completely captures the effect of weather on indoor temperatures because outdoor weather conditions constantly change and rarely repeat. The difficulty of attributing the influence on weather conditions on indoor temperature makes it difficult to isolate the effect of the state of any particular air vent register on the indoor temperature.

Our approach to overcoming this problem is to model the indoor temperature in two stages. In the first stage, we measure the rate of heat gain or loss due exclusively to outdoor weather conditions. This stage is modeled with data collected when the HVAC system is off using a linear function of current temperature. Then, when the HVAC system is turned on, we measure the *change* in the rate of heat gained or lost in a room due to the conditioned air provided by the HVAC system. We expect this change to be constant throughout the year because the HVAC system always outputs the same amount of conditioned air.

Thus, we isolate the HVAC effects by learning and subtracting out a dynamic estimate of weather effects over long periods of time.

In this paper, we present three iterations of a thermal model and analyze its accuracy in terms of predicting the effect of opening and closing various combinations of registers with a centralized HVAC system. An analysis of the HVAC system itself is beyond the scope of this paper. Performing ten-fold cross validation over three weeks of data sampled over three months, we demonstrate that even with the simplest model we can predict temperatures to within two degrees 30 minutes into the future. We focus on a 30 minute time window because longer time windows are not beneficial when making HVAC control decision. We also demonstrate that even the simplest of the three models we present in this paper is able to provide this level of accuracy allowing temperature prediction to be incorporated into an HVAC zoning controller easily and without much computation overhead.

2 Background

Heating, Ventilation, and Air Conditioning (HVAC) control systems are devised in order to maintain comfort within an enclosed space. In addition to meeting a desired temperature, this comfort is maintained by achieving a certain level of humidity, pressure, radiant energy, air motion, and air quality within a building [6]. The testbed in this study utilizes a centralized heat pump air conditioner. This is the most common method of residential air conditioning in the United States. Centralized HVAC systems do not permit fine-grained room-level control of the HVAC equipment beyond opening and closing air-vent registers that feed air into rooms. Thus, knowing the affect of opening or closing dampers is critical to the efficient retrofitting of a centralized HVAC system to enable room-level zoning.

2.1 Centralized HVAC System

The framework for the HVAC system is the air handling unit. The main responsibility of the air handling system is to deliver conditioned air throughout the building, while removing exhaust air and carbon dioxide (CO2) from the rooms. Most of the equipment is hidden from occupants, being located outside and in ducts within the building [6].

The air handling system may include fans, compressors, heating/cooling coils, and ducts, in addition to system controllers. The air handling process works in the following way: First, outdoor air is mixed with the return air of the system. The pressure of this air is determined by the supply air fan. The air is then heated/cooled to a preset temperature, and is released into specific spaces through the dampers. The exhaust air from the room is sent into the ducts according to the exhaust fan speed, and it is returned to begin the process again.

The damper is a mechanical device that allows for a variable amount of supply air to be released into a room. It consists of a thin metal sheet, rotated on an axis by an actuator. If the damper is set at 90 degrees, or 0% open, the damper is fully shut and no air is supplied to the room. When the damper is set to 0 degrees, or 100% open, the maximum amount of air is released [6].

2.2 System Logic

A centralized HVAC system can run in four possible states when heating/cooling: Float; Hold; Heat/Cool 1; and, Heat/Cool 2. Float causes the HVAC system to turn off, and hold tells the system to remain at the same temperature. Heat/Cool 1 corresponds to running the system at 67%, which provides a lower level of heating/cooling that can supply a base level of conditioned air throughout the day. Heat/Cool 2 turns on when temperature needs to be changed by a significant amount, and the system runs at 100%. The system in our testbed runs stage 2 conditioning if the current temperature is more than two degrees above/below the current setpoint [7].

2.3 Zoning

Most of the energy wasted by HVAC systems go towards heating or cooling unoccupied spaces during long periods when people use only a small fraction of a house. For instance, at night the bedrooms are used while the rest of the house is unoccupied and during the day the living room and kitchen maybe used with the bedrooms being unused for long periods of time. Zoning systems attempt to exploit this fact, and save energy for homeowners, by dividing a building into two or more zones that are controlled by separate thermostats, so that the occupants can schedule each zone to be heated or cooled separately. However, zoning systems are expensive, and are, therefore, typically only used for very course-grained zoning of the house: a typical configuration can condition the first floor living spaces separately from the second floor sleeping quarters for example. Such systems are both spatially and temporally course grained allowing large areas, in this case floors of a building, to be zoned separately and scheduled with a low frequency, for example switching between the living and sleeping areas only twice a day.

3 Problem Definition

Our problem is defined by a set of air vent dampers D and a set of temperature sensors T that are dispersed across a house (Figure 2). The dampers can be opened or closed, determining if conditioned air is delivered directly into a room. Due to the lack of thermal isolation between rooms, even if the air vent dampers of a room are closed, its temperature could still be affected by the HVAC system due to leakage from neighboring rooms. The temperature sensors monitor the temperatures at different points throughout the house. Figure 1 shows the

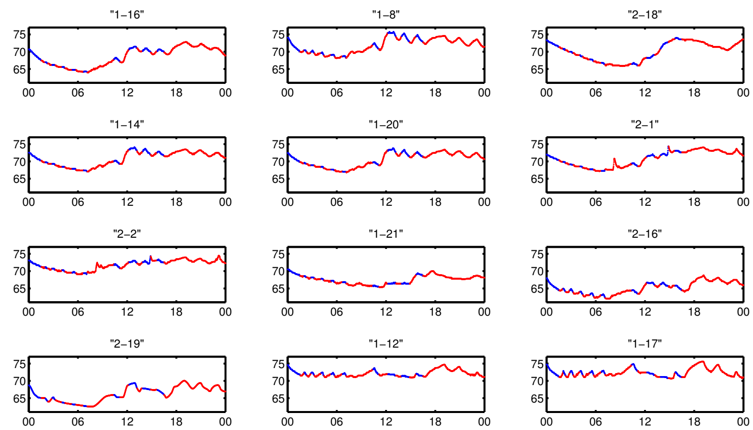

Fig. 1. The effect on temperature sensors, within a 24-hour period, of the HVAC system being on (red) and off (blue) when heating with all air vent dampers open. The locations of the twelve sensors are presented in Figure 2

readings at the twelve temperature sensors in our deployment during a day with all air vent dampers open. As the figure shows, the HVAC system being off (blue) causes drops in temperature while the HVAC system being on (red) usually causes temperature increases. We are attempting to learn and predict these effects on the temperature sensors when different sets of air vent dampers are opened and closed. In other words, we want to answer the question *"What effect does each register being open have on the reading of each temperature sensor?"* Being able to make such a prediction allows us to implement a fine-grained automated zoning controller that can dynamically alter zones within a single floor to maintain occupied rooms at a comfortable temperature while allowing unoccupied rooms to drift. Yet, answering this question is difficult due to the effect of the weather on the internal temperature of houses. Wind, solar gain, outdoor temperature, and other weather conditions have a much greater influence on indoor temperature than the conditioned air provided by an HVAC system. These weather conditions constantly change, and rarely repeat, therefore including it as part of a model is impossible without greatly increasing the complexity of the model. But, ignoring the effect of weather on internal temperature makes it impossible to isolate the effect of a particular register on a temperature sensor. Thus, a secondary question we are attempting to answer is *"Can we learn the effect of dampers on temperature sensors without knowing the weather during the training phase?"* In other words, we are attempting to capture the effect of the weather on the temperature sensor readings while ignoring the actual weather conditions, such as the external temperature or the position of the sun.

There have been a number of approaches proposed for learning the thermal response of buildings in order to control HVAC systems efficiently [8–13]. Yet, these approaches require a large amount of data or sophisticated sensors that will hinder our goal of developing a cheap and easy to install retrofit to enable room-level zoning of existing centralized HVAC systems.

4 Experimental Setup

The room-level zoning system described has been deployed in a single-story, 8-room, 1,200-square-foot residential building. A model of the home is shown in Figure 2. The hallway and porch are depicted, but not included within our analysis because of the inability to actuate temperature within these regions. The HVAC system setup is overlaid in order to show the position of vents, ducts, and the central air handler.

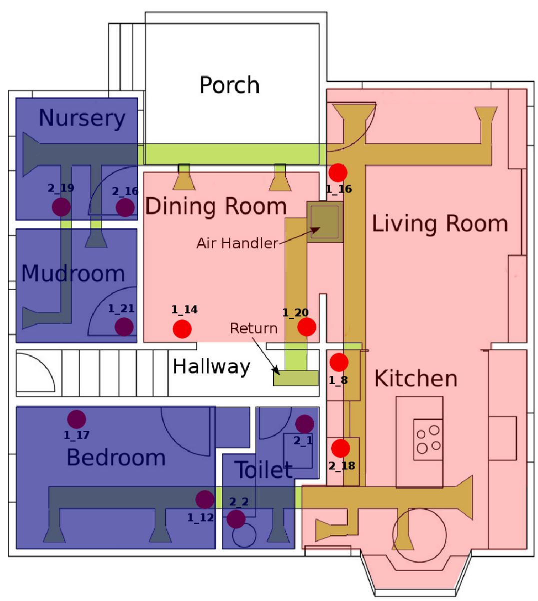

Fig. 2. The residential testbed used for this study. Red and blue overlays show an example of two room-level zones, the green ducts terminate in air vent registers that can be opened or closed, and the red circles show the locations of the twelve temperature sensors with the sensor IDs indicated.

Figure 2 shows the deployment from which data for this paper was collected. We used twelve temperature sensor deployed across the house and air vent registers that are remotely actuatable and collected data over a three month period.

Three weeks of the collected data was used for the analysis presented in this paper.

4.1 Temperature Detection

Sensors deployed throughout the building allow us to monitor the temperature and HVAC status within each room/zone. We collect temperature data at a fine granularity using temperature sensors placed at various points along the walls. In order to ensure the scalability of this system, we use 12 standard, off-the-shelf temperature sensors manufactured by La Crosse Technology [7].

One challenge with sensing temperature in this way is that temperatures are not uniform throughout the rooms/zones and along the walls. This can present problems when trying to determine the true temperature of each room. As shown in Figure 3, the placement of wall sensors has a large impact on the variability of the temperatures detected. While the sensors on the internal wall vary within the temperature range dictated by the return duct, the sensors on the external wall are subject to large temperature swings. This is because the external wall sensors pick up temperatures from outside of the building through windows, doors, and the wall itself. This is also compounded by the fact that most vents are placed on external walls, making these sensors subject to direct air from the duct [7].

Thus, we use two methods to ensure accuracy within our temperature data collection. The first is to only place sensors along the interior walls of the rooms. The second is to record the temperature as an average of these sensors, helping to detect the temperature more uniformly throughout the room.

4.2 HVAC Status Detection

The HVAC system used in this study can run in four possible states when heating/cooling: Float; Hold; Heat/Cool 1; and, Heat/Cool 2. Data on these system states are collected by interfacing with a standard internet-controlled thermostat manufactured by BAYweb. These stages are described in detail in the following section.

5 Model of Temperature Dynamics

The parameters of the model include the position of the damper, temperature, system status, and time. These values are recorded through a wireless sensor network deployed in the testbed and stored in a database. The temperature values are measured in degrees Fahrenheit, and the damper positions take one of two values: 0 (closed) or 1 (open 100%). The system status allows us to see whether the system is in off, heat/cool 1, or heat/cool 2 mode. An example of the damper, temperature, and system status for one room is shown in Figure 3.

In analyzing this system, we explore a number of different models. Three iterations of our final model are shown in the following sections. Each is a dynamic,

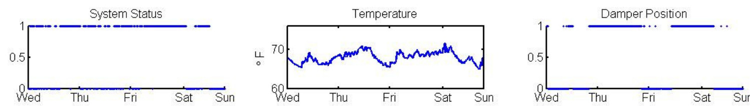

Fig. 3. The system status (on/off), temperature (°F), and damper position (open/closed) for one room in our testbed over the period 11/30/2011-12/04/2011.

linear model that is developed in two stages. The first stage aims to estimate the effects of heating/cooling due to external factors such as solar radiation, wind, and cloud coverage. This effect is calculated when the system is turned off, and the values are then used to develop the model when the system turns back on. This two-stage approach allows us to compensate for external factors without having to measure them directly. Furthermore, the results allow us to predict temperature dynamics due to the HVAC configuration with greater accuracy.

$$dT_k/dt = \alpha T + \beta D \tag{1}$$

The models we discuss follow the same format (Equation 1) in which the temperature of a specific room T_k over time t is a result of external factors (calculated through α), and the current damper configuration, D. The three iterations of this model differ in the way that the external factor coefficient, α, is calculated. These differences are as follows: 1) The first iteration calculates a universal α value by pooling the data when the system is off. 2) The second iteration calculates a constantly changing α value when the system is off, and uses this constantly calculated α value in the model when the system turns on. 3) The third iteration adds to the model complexity by using universal α values for all neighbors $T_1, ..., T_n$ of the temperature in room k, T_k.

5.1 Static α

The first iteration of the model we describe is one in which the α values, which estimate the temperature change due to weather patterns, are constant throughout the day. In order to calculate these values, we pool the data from times when the system is off together and fit one α value across all timesteps for each of the n rooms. This value is calculated through linear regression, and assumes that the heat load due to weather remains relatively constant throughout the day.

5.2 Dynamic α

In the second iteration, we explore the idea that the heat load due to weather conditions may be changing continuously throughout the day. In order to do this, we calculate a dynamically changing α value for each off segment, and include that value in the on segment that directly follows it. This method aims to compensate for weather by assuming that the heat load due to weather changes significantly throughout the day, but by very little between one cycle of the system.

5.3 Adjacency Model

The third iteration increases the complexity of the first by including the other n rooms into the model. This assumes that the current temperature of the room is affected not only by its own weather conditions, but also by the temperature dynamics within the other rooms of the building. This model also calculates the α values universally through linear regression. The form of this room adjacency model is as follows:

$$dT_k/dt = \alpha_1 T_1 + \alpha_2 T_2 + \ldots + \alpha_n T_n + \beta D \tag{2}$$

6 Results

We compare the three iterations of our model described in section 5 using 21 days worth of data tested with 10-fold cross validation which involves randomly dividing the 21 days of data into ten equal sets, training the model using nine of those sets, and testing with the remaining set. All combinations of nine sets for training and one set for testing are used. The 21 days we have selected for model development and testing have been sampled from 3 months worth of data between October and December 2011. Using the training data, we develop the β values for the model. We then use these values with the α value scheme dictated by the model iteration in order to predict temperatures when the system turns on.

6.1 Prediction

Our predictions assume that temperature grows linearly when the system turns on as a result of the current damper configuration and the previous weather patterns estimated through α. Though temperature dynamics within a building are often nonlinear, we find a reasonable estimate by predicting temperature linearly into the future. This is because the temperature and airflow of the system operate within a narrow regime, making it reasonable to approximate change with a linear model. An example of a prediction 30 minutes into the future is shown in Figure 4. Here, the blue lines represent the actual temperatures and the red line plots our prediction. The solid blue line shows the temperature when the system is off, and the red/blue dashed lines show the predicted/actual temperatures when the system has just turned on.

6.2 Error Metric

One difficulty in determining the effectiveness of these models is that we aim to use them to predict temperatures at more than one timestep into the future.

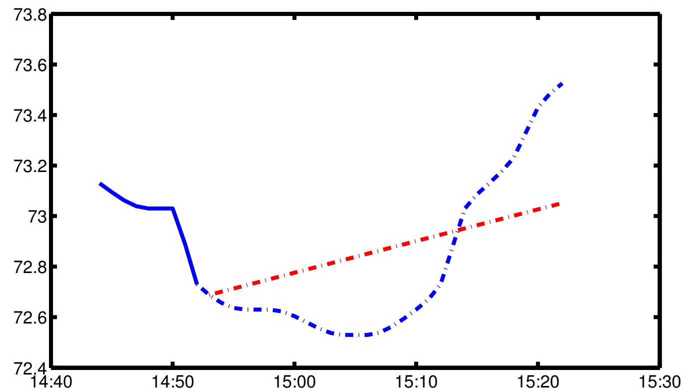

Fig. 4. An example of a prediction made for temperature up to 30 minutes into the future after the system turns on. The solid blue line shows the actual temperature when the system is off; the dashed blue line shows the actual temperature when the system is on; and the dashed red line shows temperature predicted after the system has just turned on.

This involves calculating predictions at each point that the system is on, up to t minutes into the future until the system turns off again.

The error metric that we have chosen for this comparison is to determine the distribution of prediction error as we predict t minutes into the future. For each minute, t, we calculate the mean and standard deviation of the prediction errors t minutes away from the initial time. The results from these analyses for the static α, dynamic α, and adjacency model are shown in Figure 5, Figure 6, and Figure 7 respectively. These results are calculated on a per-sensor basis for each of the 12 sensors in the 7 rooms of the building.

Visually examining the error distributions highlights a few important things about the model. One is that the variance of the errors tends to increase as we predict further into the future. The error can get quite large in some places, particularly in the dynamic α model. However, most of the values for each model remain within 2 degrees for the 30 minute prediction. This is a reasonable interval with which to enable the control of the system that we aim to accomplish.

The results from this analysis also indicate that the simple, pooled α model performs better than the dynamic model. This may be counterintuitive since weather tends to change significantly throughout the day. However, because of the window we are looking at and the narrow range of temperature change, it is reasonable that this model should perform well. It also has the added benefit of being computable and easy to implement within a control setting.

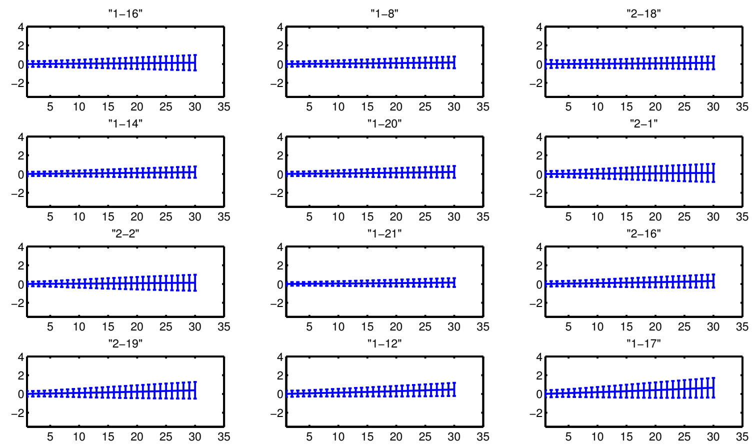

Fig. 5. Error distribtuions for the static α model, up to 30 minutes into the future. The locations of the twelve sensors are presented in Figure 2

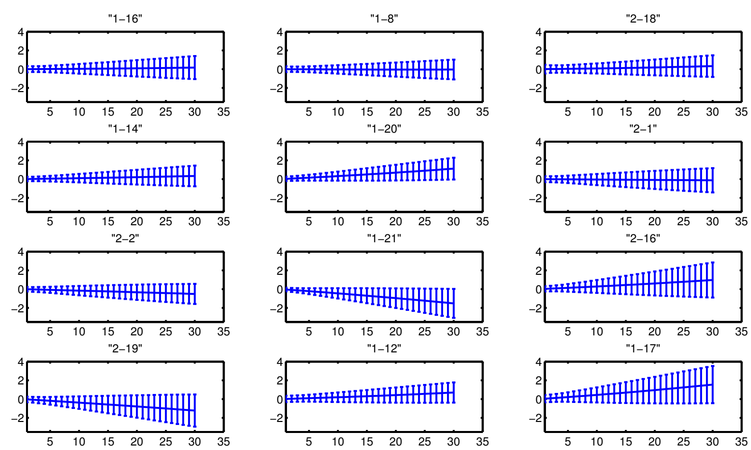

Fig. 6. Error distributions for the dynamic α model, up to 30 minutes into the future. The locations of the twelve sensors are presented in Figure 2

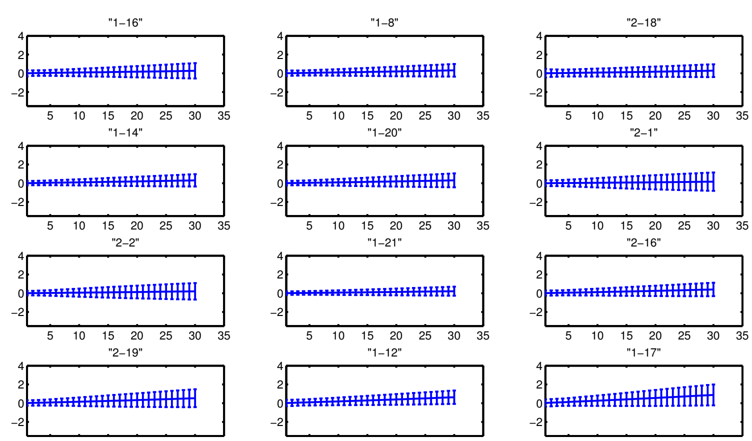

Fig. 7. Error distributions for the adjacency model, up to 30 minutes into the future. The locations of the twelve sensors are presented in Figure 2

7 Work-In-Progress

An observation we made with the model presented in this paper is that its linear nature fails to capture the mixing period experienced when the HVAC system first turns on. As Figure 4 shows, the temperature measured at a sensor continues to drop for about twenty minutes after the HVAC system is turned on before it begins warming up. This could be caused by the time taken for the conditioned air to sufficiently mix with the cold air in the room before the increase in temperature is detectable by a sensor and the absorption of heat by the structure of the room, such as walls and floors, as well as objects in the room such as furniture before the air get heated because these objects have a higher heat capacity than air. In order to capture this mixing period, we modify the thermal model by introducing a variable γ that varies with time and influences the effect the conditioned air from the HVAC has on the temperature sensor.

We estimate values of γ by creating a set of equations, such as the following, at various times from the time the HVAC turns on until 30 minutes into the future:

$$T_1 - T_0 = \alpha + \gamma_1 \beta D \tag{3}$$
$$T_2 - T_0 = \alpha + \gamma_2 \beta D \tag{4}$$
$$T_3 - T_0 = \alpha + \gamma_3 \beta D \tag{5}$$

Solving these equations for historical temperature data and HVAC state provides a set of γ values. Using these γ values a new iteration of the model can be specified as follows:

$$dT_k/dt = \alpha T + \gamma_k \beta D \tag{6}$$

We are currently in the process of training and evaluating this model.

8 Conclusions

We have presented our residential testbed, studied the characteristics of the dual stage HVAC, identified and analyzed mathematical models of the system, and discussed the impact of our results. The two-stage, dynamic model that we have developed provides an accurate way to predict the temperature in a zone based on a few, accessible parameters in the system. It also allows the calculation of highly variable terms, such as the heat load due to solar radiation, wind, and cloud coverage, without the need to explicitly measure these terms.

These results will be used in future work in order to develop a new, energy efficienct control scheme for the system. The model gives us better insight into the dynamics of the control scheme and allows for a more efficient design. This control scheme may then be used to create a more energy efficient design for similar HVAC units. This type of work is a crucial step in the developing the type of energy-agile systems that can ultimately be used to quell our dependency on fossil fuels.

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