TOWARDS BETTER MODELING OF RESIDENTIAL THERMOSTATS

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ABSTRACT

Thermostats are notorious for being difficult to use. Consequently, heating is manually controlled by occupants in most homes, including those with programmable thermostats. Conventional modeling approaches fail at capturing behavioral elements by relying on fixed setpoint schedules. To accurately assess the energy impact of thermostat operation requires two changes to the way simulations are carried out. First, thermostat setpoint programs must be defined based on how thermostats are actually operated instead of the usually assumed ideal behavior; and second, realistic occupancy schedules must be adopted instead of average schedules. This may require layering of behavioral logic atop thermostat logic. In this paper we present an approach for doing this using Energy Plus and American Time Use Survey (ATUS) data, together with some examples.

INTRODUCTION

For more than 30 years studies have examined occupant interaction with thermostats, more recently focusing on programmable thermostats (PTs) in particular. Their aim is usually to determine usability or existence of energy savings. Results are conflicting, where some researchers find that PTs result in savings, others find the opposite. Often this is due to occupants' lifestyle or behavior, which can vary up to 26% (van Raaij and Verhallen 1983). This ultimately presents a challenge to those who endeavor to predict energy consumption through modeling, as this behavior does not conform to the rigid schedules currently input into simulation software. In response, advances in probabilistic and stochastic algorithms have been made.

Perceptions of how HVAC systems work play an integral role in how an occupant interacts with the system (Peffer et al. 2011; Meier et al. 2010). Meier et al. cite some misconceptions including:

- Thermostat is simply an on/off switch
- Thermostat is a dimmer switch for heat (valve theory)
- Turning down the thermostat does not reduce energy consumption (or not substantially)
- Boiler thermostat is used to change the temperature in the room (as if it is a room thermostat)
- People are afraid of using PTs (unknown terrible consequences)

Others regard a thermostat as an accelerator, where turning it higher will heat faster (Kempton 1986). This is identical to the valve model. Still, others believe that turning up the heat in a cold space will consume more energy initially; therefore they maintain a constant temperature to avoid this *surge* in energy usage.

Hoes et al. (2009) cite Degelman, who finds that occupant behavior has a greater impact on energy performance than the thermal processes of the façade. Their use of a stochastic sub-hourly occupancy control (SHOCC) model assumes an *active* user, or one who wants to save energy by operating windows and lights. The SHOCC, better for lower occupancies like residences, was used in conjunction with the User Simulation of Space Utilization (USSU) model, better for more sporadic occupancies such as open offices, to represent occupant behavior. The need for more advanced behavioral models was determined via flowchart, as presence and interaction are two major components. They also show that design robustness plays a factor.

Richardson et al. (2008) present a high-resolution model for modeling occupancy in UK homes based on UK Time Use Survey data that relies on Markov-Chain techniques to generate occupancy profiles that are statistically similar to that of the survey data. This method is the most similar to the one we present.

Haiad et al. (2004) found 59 models to represent human behavior, leading to over 300,000 simulations. They acknowledge that for the average energy investigation, this is prohibitive; however, their study in California, begins to examine thermostat interaction more precisely. They list the average heating and cooling setback temperatures, for example. Woods (2006) also considers average heating setpoint temperatures by month and models behavior using Shannon entropy, which examines consistency of the setpoint temperatures.

Nevius and Pigg (2000) found that even with PTs, 17.2% and 26.7% of occupants do not use setbacks for night and day, respectively. According to a survey of 20 low income homes in Wisconsin (Meier et al. 2010) 85% claimed to use the programmable features of their thermostat; however, photographs of their thermostats belied their reports, as only 30% were programmed, 45% were on hold, 5% were off. Their online survey found that 89% of respondents rarely or never used PT to set a weekly or weekend program, and 54% used the on/off switch at least weekly.

Tanimoto et al. (2006), assess occupant behavior, but investigate all activities in a household, not adjustment of a thermostat, by developing a probablistic model based on time use data from Japan. Yamaguchi et al. (2011) agree that to more accurately represent occupant behavior in high resolution, stochastic modeling and time use data must be used. This is a good start. Similarly, insight can be gained from models for occupants' behavior with operable windows, as in Yun et al. (2009), which also employs Markov chain and Monte Carlo models. One major drawback of these models is the inability to model day-to-day patterns. Page et al. (2007) take Tanimoto et al.'s approach one step further by considering time-independence, unlike transition probability based approaches, in which the current state of behavior is highly dependent on the state immediately-before. They call this a *mobility parameter* and it is used to consider absences of more than one day.

Overall trends are seen between the papers. Yun and van Raajn classify users into behavioral categories – passive, average and active – not unlike the personas explored by Goldstein et al (2010). Occupants' attitudes towards energy savings were also considered, with conflicting conclusions – being pro-energy efficiency did not always lead to savings. Cross and Judd, and Meier et al., give percentages of participants who behave in a particular manner. Nevis and Pigg, Haiad et al., and Woods give setpoint temperatures for certain periods of time. Many authors report users being confused by their thermostat, while the amount of available features is increasing.

MODELING OCCUPANT BEHAVIOR

Few occupants operate their thermostats predicatbly. Preliminary data from an ongoing thermostat field study corroborate this. Not only do people fail at programming thermostats correctly, they also operate them inconsistently. This is not surprising given the prior work describing how people mentally model thermostats.

Accordingly, we envision that it is possible to create logical models based on statistical variability to better-simulate the action of thermostats in households. Subsequent field testing could enable the determination of the prevalence of each mental model, thus enabling more accurate impact analysis.

Two main kinds of behavioral interaction may take place with a thermostat. One has to do with making adjustments to the thermostat, e.g., overriding the current setpoint. And the other has to do with the actual programming of the thermostat. In this paper, we deal only with manual adjustments to thermostats, however thermostat programs could easily be integrated into this methodology.

Behavior-driven variability may occur in several ways. First, in the temperatures that are selected, and second, in the frequency with which a thermostat is adjusted. The temperature selection may depend on several factors, such as who is present, what clothing is worn, and a person's beliefs about how a thermostat works.

A given household may have a typical range of prefered temperatures. In another case, the occupants may operate the thermostat with a consistent temperature overshoot (following the *valve* or *accelerator* mental model of thermostat operation), followed by a subsequent overcorrection (e.g., opening the window, or shutting off the heating system completely). In yet another case, a family may operate their thermostat according to a permanent temperature hold, or perhaps according to a rationally-set program. Each of these behaviors will produce a different energy consumption result, and many will produce a substantial variation.

Instead of oscillating between two fixed setpoints, users may choose a temperature based on random factors that cannot be known within the scope of a building simulation. To account for this variability, setpoint temperatures may be modeled as a random variable within a typical range. With random number generators present in most spreadsheet programs, such behavior can be readily modeled.

In addition to user behavior, one must also be able to model when the behavior takes place. Most importantly, with the exception of highly-advanced thermostats, users can only adjust the thermostat when they are at home. Behavior could be modeled such that the thermostat is adjusted when someone leaves or enters the house. Alternatively, a specified number of random adjustments could be made while occupants are at home. In the next section, we look at ways of modeling occupancy in better detail.

MODELING OCCUPANCY PATTERNS

Average schedules are not typical schedules. Normally, modelers define fixed schedules for thermostat setpoints and building occupancy based on average or ideal conditions. Figure 1 shows the likelihood of a person being found at home according to the time of day (BLS 2011). Yet, on a given day, actual occupancy patterns can differ substantially from the average. People come and go. Each line in Figure 2 represents the binary occupancy patterns of 20 individuals on a given day.

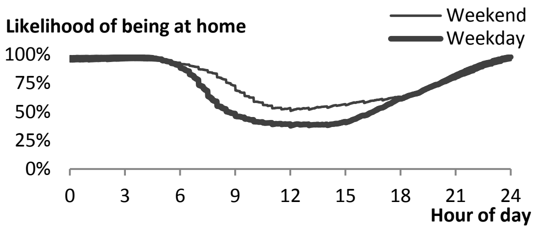

Figure 1 Average probability of being at home

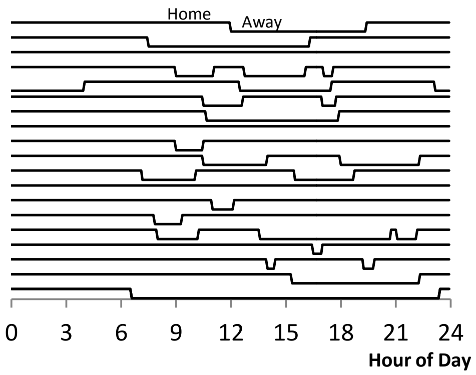

Figure 2 Actual occupancy patterns of 20 individuals

Since occupancy schedules can differ substantially from day to day, so can the need for heating or cooling. This is especially true when thermostats are operated manually according to desire for comfort while at home. From a modeling perspective, this is important, because buildings have a thermal memory due to the heat capacity of materials. This is why having a setpoint of 60 degrees during the night and 80 degrees during the day is not the same as having a setpoint of 70 degrees all the time. Variability in thermostat setpoints, as caused by occupants, may significantly impact energy use predictions. This can lead to incorrect conclusions about the effectiveness of programmable thermostats.

To model when people are at home, we used data from the American Time Use Survey (ATUS) to determine both actual and average occupancy behaviors across the survey population. Each survey participant recorded the time, duration, and location of all their activities throughout one day. Figure 3 represents the daily schedules of all 13,259 survey participants, with each column representing one person's day from morning to evening. The lower graphs show the variability among different kinds of days (e.g., weekdays, weekends, and holidays). A standard occupancy schedule does not capture this variability.

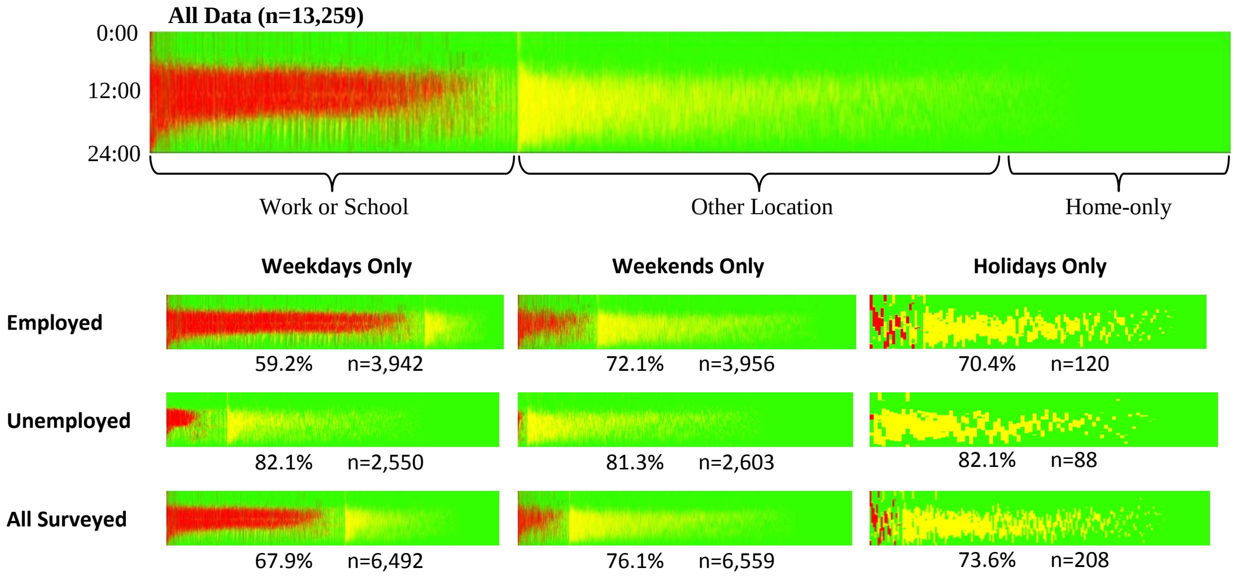

Figure 3 Daily whereabouts of Americans: Each vertical stripe represents one person's day. Green= at home; Red=at work or school; Yellow=other location. Percentages= time spent at home.

A model developed by Richardson et al. (2008) can create synthetic daily occupancy patterns similar to those in Figure 2, based on weekend or weekday patterns and household size. Taking this technique one step further, it is possible to focus on subsets of the population to develop even more representative schedules, akin to the *personas* explored by Goldstein et al. (2010) for commercial buildings. Such finer-grained models can better address specific demographics, such as those who work night shifts, live alone, are retired, or travel frequently. As an example, the lower portion of Figure 3 shows the differences in reported occupancy schedules between the employed and the unemployed. Whereas the unemployed spend about 82% of their time at home, regardless of the day of the week, the employed are at home 72% of the time on weekends, and 59% of the time on weekdays. Such differences in occupancy could produce significantly different temperature setpoint schedules, resulting in different estimates for energy use.

One way of modeling occupancy is by randomly sampling daily schedules from the ATUS dataset to populate a spreadsheet of hourly occupancy values. This is the most straightforward way. Sampling can be done restrictively. You could, for instance, select daily schedules by matching specific critiera of the responders, such as household size, employment status, or income. Sampling based on weekend or weekday may or may not matter, depending on the criteria.

Another way of modeling occupancy is to develop a Markov-Chain model of state-transitions. For example, you could calculate the probability of occupancy changing from one state to another from one hour to the next, like Yamaguchi. This allows the creation of new occupancy patterns that have the same characteristics of those from the survey. The advantage of this approach is that once the state transition probabilities are determined for the population you wish to model, you no longer need to rely on the original dataset. The disadvantage is that it requires more analytical effort.

For the simulations in this paper, we use both fixed and sampled schedules.

SIMULATIONS

Here we illustrate the modeling approach with a few examples, all of which are based on the same building input file and climate (Zone 5A, Chicago). For each case we focus only on annual natural gas heating energy (GJ). For simplicity, in the fixed schedules, we ignore the differences between weekends and weekdays.

The input file represents a 2 bedroom, 1 bathroom, single-story residential building of 1,000 ft^2 (40ft x 25ft), created using BEopt (NREL 2012) default parameters and exported as an EnergyPlus IDF file.

Next, we modified the thermostat setpoint schedules in the IDF file to reference an external spreadsheet of hourly values. Each column of this spreadsheet represents a unique annual temperature schedule (8,760 rows, one for each hour of the year).

Using a Python script, we generated a batch of input files, each pointing to a different column in the thermostat spreadsheet. With the Energy Plus grouping feature, we batched together all the input files and ran them at once.

Finally, using another Python script, we extracted the heating energy values from the output spreadsheets for analysis.

Once set up, the entire process can be repeated in a matter of minutes. Experimenting on the effect of different schedules can be done simply by modifying the temperature schedule file and re-running the simulation batch. For reference, simulating 100 schedules in the simple residential building takes about 10 minutes on a modern laptop.

Fixed Occupancy Schedule Examples

Ex. 1: Fixed Setpoint

As a baseline, we begin with a simple parametric simulation to model the dependence of annual heating energy demand on a fixed setpoint temperature. Unsurprisingly, the results in Figure 4 indicate the rising need for heating energy as setpoint temperature increases.

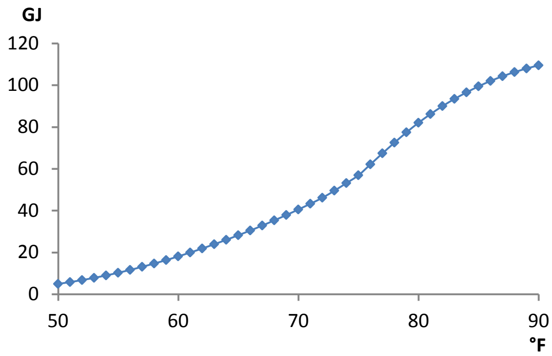

Figure 4 Heating energy vs. fixed setpoint temperature

Ex. 2: Variable Setpoints, Random Values

In this case, we assume that at 8am and 6pm daily, someone in the household adjusts the setpoint to a random integer value between 65 and 75 degrees inclusive. We repeat this experiment 100 times to determine the influence of random behavior on energy consumption.

The average setpoint temperature was the same as in Ex. 1 (70.0°F), yet the calculated energy consumption was always higher (3.7% higher on average) than for fixed setpoints as shown in Figure 5. The x-axis temperatures in this figure represent the average setpoint temperature during the heating season (Oct. 1 to May 31).

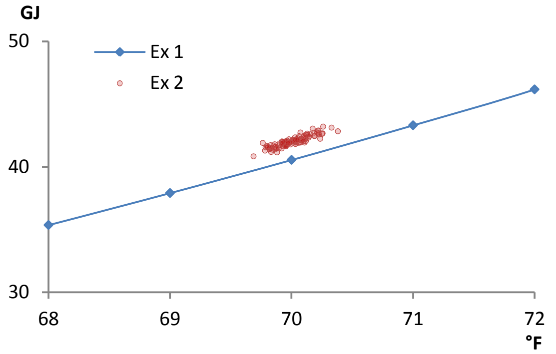

Figure 5 Heating energy vs. setpoint temperature

Ex. 3: Daytime Off, Ideal Behavior

In this example we model the ideal behavior of someone who leaves for work at 8am and returns at 6pm daily. Instead of using a setback temperature, this person turns off their heating system completely.

Ex. 4: Nighttime Setback, Ideal Behavior

In this example we model an ideal night setback to 60°F, beginning at 11pm and ending at 6am. During the remaining hours, the temperature is set to the value shown on the x-axis of Figure 6. Not surprisingly the nighttime setback provides better savings than the daytime setback, since daytime temperatures tend to be warmer and because of solar gains.

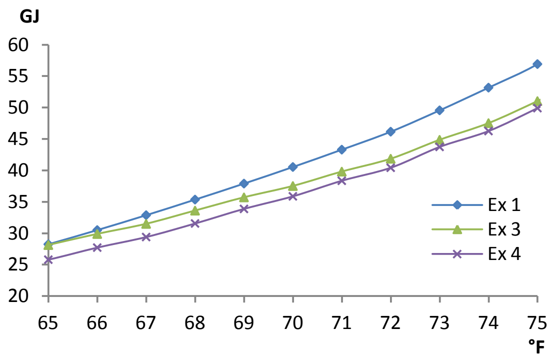

Figure 6 Heating energy vs. setpoint temperature.

Ex. 5: Nighttime Setback, Realistic Behavior

In this example, we model the same case as in Ex. 4, but with the introduction of variable occupant behavior. Here we assume the occupant has a 50% chance of remembering to turn down the heat to 60°F at 11pm, and at 6am, the temperature is reset to 70°F without fail. The model is run 100 times to show the variation due to chance.

The results in Figure 7 show the significance of behavioral variability. As expected, the results lie between the fixed and ideal setback examples, yet the spread between maximum and minimum energy consumption spans about one third of their difference.

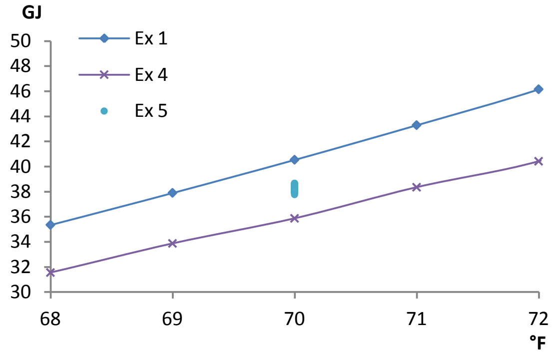

Figure 7 Heating energy vs. setpoint temperature

Variable Occupancy Schedule Examples

Ex. 6: Realistic Occupancy, Ideal Setback

In this example, we created 100 unique annual schedules of 365 unique workdays by randomly sampling daily schedules from the population of employed survey responders. Again, we neglect weekends in this study to keep things simple. To model the ideal behavior with the random schedule, we assign 70°F whenever the person is home and 60°F when they are away.

Results in Figure 8 show the best savings yet, but again with a significant range in variability. At worst, this strategy appears to perform only slightly better than the case of ideal nighttime setback, but at best it does 5% better.

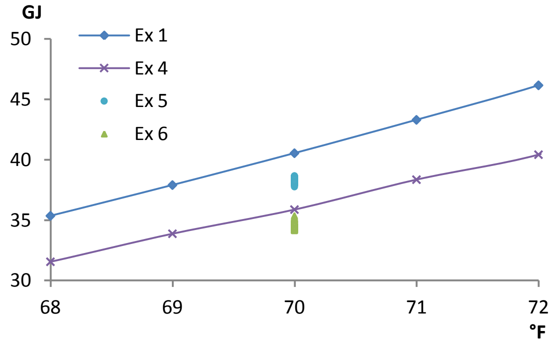

Figure 8 Heating energy vs. setpoint temperature

Analysis of the 100 generated schedules revealed that the entire sample was at home 59.8% of the time, compared with 59.2% for the raw data, indicating that the sampling technique is fairly representative. If higher certainty is desired, more trials could be run.

Ex. 7: Realistic Occupancy, Variable Behavior

In this final example, we model schedules based on both the realistic occupancy schedules of Ex. 6 and the irregular behavior of the occupants.

Here we assume that whenever occupants leave the house, they remember 50% of the time to set the thermostat to a random temperature between 59-61°F, otherwise the setpoint remains as it was. When people return home, they randomly adjust the temperature to a value between 65 and 75°F, where it remains until they leave again.

Figure 9 shows that this case has the widest range of variability among the cases investigated. The results are far worse than the ideal case of Ex. 6, even though the same set of randomized schedules were used in each case. The difference between the means of Ex. 6 and 7 could represent the potential energy savings benefit of a smart thermostat as compared to typical operation.

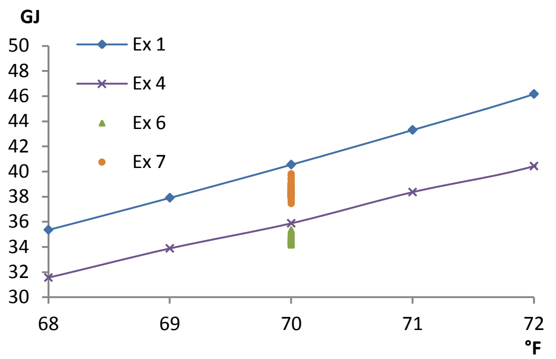

Figure 9 Heating energy vs. setpoint temperature

CONCLUSIONS

In this paper we have demonstrated a practical stochastic approach for modeling occupant behavior and realistic occupancy patterns, using existing tools and readily available data.

Variations in energy use caused by irregular occupant behavior and occupancy can be significant (on the order of 5%), making it difficult to properly evaluate true savings of some energy efficiency measures. Using this approach can lead to better understanding of the building-user interaction, which may ultimately lead to better strategies for reducing energy consumption in buildings.

Data from future thermostat field studies (one is currently underway) will help guide the selection of the probablistic parameters that will make these models even more useful.

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