THE IMPACT OF THE BUILDING OCCUPANT ON ENERGY MODELING SIMULATIONS

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ABSTRACT

Uncertainties regarding behavior of building occupants limit the ability of energy models to accurately predict actual building performance. Initial results show that predicted energy consumption changes by more than 150% using all high or all low values for what experts believe reasonably represents occupant behavior. Although numerous sources of modeling inaccuracies and over-simplifications exist, more research is needed to fully evaluate the sensitivity of energy modeling results to variability in occupant behavior. This study analyzes existing energy programs and identifies schedule and load parameters currently used to characterize building occupancy. It then performs a crude sensitivity analysis that shows the impact of the uncertainty with respect to changes of individual values for these parameters. It identifies the most significant individual contributors to variability in results and identifies directions for future research. The eventual goal of this work is to increase the accuracy of energy modeling simulations through improvements to the model of building occupancy.

KEY WORDS

Occupant, Energy Modeling, Uncertainty, Occupant Behavior, Energy Simulation.

INTRODUCTION

Energy modeling simulations used in current design practice typically provide deterministic (singular, replicable) results of varying accuracy. Experts polled by the authors estimated that energy modeling accuracy ranges from +/- 10 - 40% for non-residential models and general industry consensus is that comparisons of predicted performances are more useful than the absolute values themselves. Sources of errors range from overly optimistic assumptions about construction quality and equipment performance to unknowable and uncertain specifications such as actual weather conditions, exact "as-built" conditions etc. to over-simplified modeling assumptions or algorithms, such as fully-mixed air, or the inability to model radiant surfaces. In general, reliability can be closely linked to the judicious choice and quantification of model parameters, (de Wit, 2001). Several sensitivity studies have already been dedicated to analyzing the uncertainty of energy modeling output based on expert assessed ranges of specific inputs (ventilation rates, window shading etc.) in an attempt to either identify dominant sources of impact (de Wit 2001) or to tune modeling accuracy (Bourgeois, D. et

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al 2004). This paper is an initial investigation of the impact of the uncertainties associated with occupant behavior on energy modeling results.

The dominant energy modeling simulation programs in use today (DOE-2 and BLAST) have calculation engines that were primarily developed in the early 1970s. Industry consensus is that opportunities exist for significant improvement to these tools (Crawley et al 2001), and the U.S. Department of Energy is currently sponsoring the development of EnergyPlus and other energy modeling projects. While this paper uses DOE-2 to perform its initial sensitivity analyses, the overall goal of the analysis is not to focus on any one simulation tool or to identify specific improvements for DOE-2. Rather, the goal of this paper is to establish theoretical and practical bounds for the sensitivity of energy simulation tools to occupant behavior, and to identify areas for productive research in the future.

To date, little research has been done to specifically address the uncertainties introduced to energy model simulations from variable occupant behavior. However, empirical data shows that the energy use of different occupants living in identical residential units can vary by as much as 200-300% (Lutzenhiser, L., 1987) and that consumption varies considerably in both end-use type and load shape. This paper begins to quantify the impact of the uncertainty introduced from occupant behavior assumptions on energy modeling results (total energy consumption, and peak energy consumption) using the uncertainty analysis phases outlined by Macdonald I. A., et al (1999) of first defining the uncertainties in a database, performing multiple simulations of the (perturbed) models, and analyzing the results. Schools were chosen as the domain for this study since, as a building type, they are regularly and frequently subject to variable occupancy, and, as such, provide a valuable opportunity for validation in the future. This study uses a model of an elementary school in cold (Denver, Colorado) and hot (Sacramento, California) climates as its basis. In this paper, we first review the parameters and values chosen for this model. Next, we review the result of a sensitivity analysis based on these parameters and values. Finally, we discuss conclusions and next steps in our effort to define a better model of the building occupant to lead to better predictive energy modeling and simulation analysis.

DEFINING UNCERTAINTY FOR OCCUPANT VARIABLES

The first step in crude uncertainty analysis is the assessment of plausible ranges of values for model parameters (de Wit 2001). In this case, it was first necessary to identify the salient model parameters characterizing the building occupant. Through analysis of energy simulation tools (Energy-10, DOE-2.1e, EnergyPlus, BLAST), a full list of occupant and operator (building manager) inputs was established including a list of equipment set points and operational parameters over which building users have jurisdiction. This paper limits the study of occupant inputs to those things impacted by the presence or actions of the typical building occupant in elementary schools using DOE-2 as the energy simulation tool. The medium values for these parameters were established through a review of California's Title 24 code requirements as it specifies occupant behavior. In addition, experts were polled to confirm the totality of the inputs and to establish low and high ranges for the targeted inputs in regard to an elementary school occupancy type. These identified ranges are intended to represent reasonable estimates of typical occupant behavior (changes to thermostat settings, opening windows, student naptime in classrooms etc.) rather than simulate the full range of “real-life” impacts that could include equipment override or poor building maintenance (taping over daylight sensors, ignoring economizers stuck open etc.). Schedules were selected to model typical variation in school daily operations, although the authors acknowledge that schools can also operate on twelve-month calendars or with extended night school hours.

The following ten parameters and values were identified to represent the current model of the occupant in DOE-2 energy simulations. For DOE-2 in general, variability for energy model inputs is defined by assigning different sets of 24-hour diversity factors for weekdays, weekends, holidays, etc. to the maximum load of each end-use (occupants, lighting, equipment, etc.). Table 1 lists the schedules that are used to model occupant behavior and Table 2 lists the loads that are directly or indirectly influenced by the actions or the presence of the occupant.

Table 1: Occupant Schedules

DOE-2 Parameters	Description	Ranges
LIGHTING-SCHEDULE	*Lighting schedule* – hourly assignment of percentage light output (% of W/SF)	Low: Half-day, 9 month calendar Medium: Full-day, 9 month calendar High: Full-day, 9 month calendar, before and after school programs
EQUIP-SCHEDULE	*Equipment schedule* - hourly assignment of percentage plug load usage (% of W/SF)	Low: Half-day, 9 month calendar Medium: Full-day, 9 month calendar High: Full-day, 9 month calendar, before and after school programs
PEOPLE-SCHEDULE	*Occupant Schedule* - hourly assignment of percentage of population present (% of maximum population)	Low: Half-day, 9 month calendar Medium: Full-day, 9 month calendar High: Full-day, 9 month calendar, before and after school programs
HOT-WATER-SCHEDULE	*Hot water schedule* - hourly assignment of percentage of hot water use (% of BTU/h)	Omitted*

* Domestic hot water usage in elementary schools deemed insignificant.

Table 2: Occupant Loads

DOE-2 Parameters	Description	Ranges
HEAT-SET-T / COOL-SET-T	*Temperature setpoints* - the temperatures at which active heating or cooling begins and ends.	Low: 68 °F / 78 °F Medium: 70 °F / 74 °F High: 71 °F / 73 °F

AIR-CHANGES/HR	*Infiltration rate*- generally quantifies the tightness of the building envelope, but also includes opening of windows and doors by the occupant.	Low: .2 AC/HR Medium: .5 AC/HR High: 2 AC/HR
AREA/PERSON	*Occupant density*- people per area based on 10, 24, or 36 students in a 960SF classroom.	Low: 10 people/ 1000 SF Medium: 25 people/ 1000 SF High: 37.5 people/ 1000 SF
PEOPLE-HG-LAT	*Latent heat gain*- change in moisture content produced by sedentary to active school children.	Low: 105 BTU/hr per person Medium: 155 BTU/hr per person High: 600 BTU/hr per person
PEOPLE-HG-SENS	*Sensible heat gain*- change in temperature produced by sedentary to active school children.	Low: 200 BTU/hr per person Medium: 230 BTU/hr per person High: 300 BTU/hr per person
OA-CFM	*Ventilation rate*- supply of air based on 15 – 20 CFM per student in classrooms containing 10, 24, or 36 students.	Low: 0.15 CFM/SF Medium: 0.38 CFM/SF High: .75 CFM/SF
EQUIP-LOAD	*Equipment load*- equipment plugged into receptacle outlets. (W/SF)	Low: 0.1 W/SF Medium: 1.0 W/SF High: 2.0 W/SF

Representative climate data for Denver, Colorado and Sacramento, California were used to run the energy simulations. Two climates were studied since former research (and logic) shows that buildings where heat loss dominates the building load are more sensitive to thermostat settings, whereas buildings that are dominated by heat gain, are more sensitive to occupants and their activity levels (Fagerson, 1984).

Simulations were run setting all inputs to medium values and setting one occupant input parameter to either a high or a low value, and normalized energy use and normalized peak demand were plotted. While further study will conduct a more complete search through the space, these ranges give an overall sensitivity profile for the parameters and values chosen.

RESULTS

Figures 1-4 summarize the results for total annual energy use as well as total peak demand for both climates.

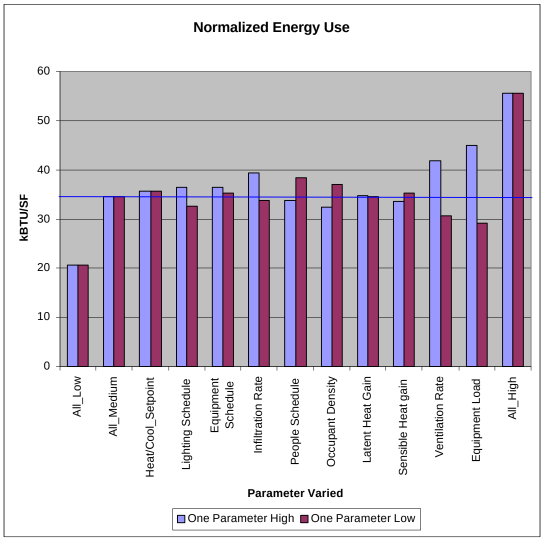

Figure 1

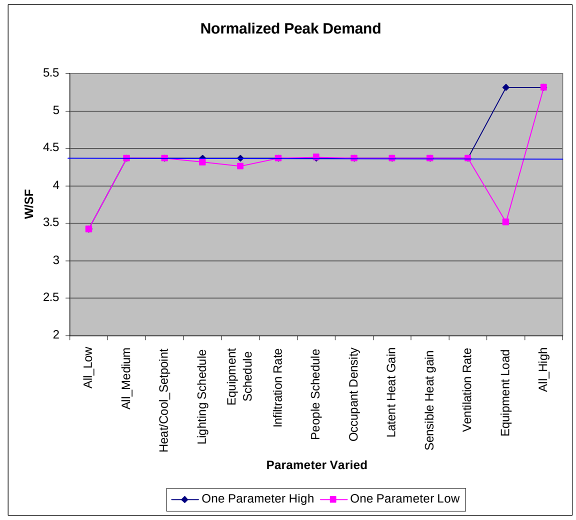

Figure 2

Energy Results for Warm Climates: Figure 1 shows variability of normalized annual energy use for warm climates setting one occupant parameter to high (blue) or to low (red) relative to all-medium values (blue line). Estimated annual energy use with all parameter set to low (left) or to high (right) are also shown. Figure 2 shows variability of normalized peak demand for warm climates setting one occupant parameter to high (blue) or to low (red). Estimated peak demand with all parameters set to low (left) or to high (right) are also shown.

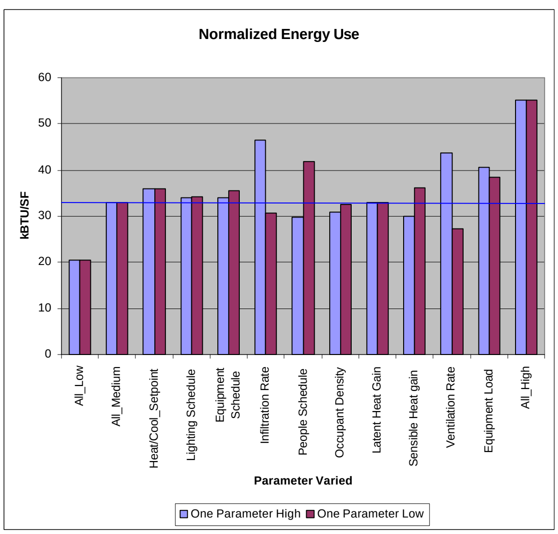

Figure 3

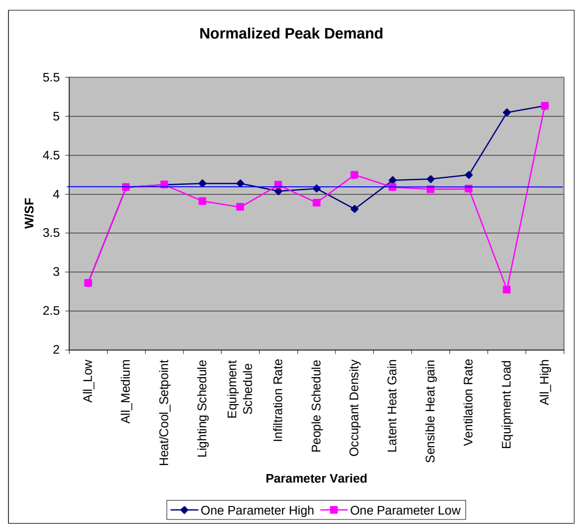

Figure 4

Energy Results for Cold Climates: Figure 3 shows variability of normalized annual energy use for cold climates setting one occupant parameter to high (blue) or to low (red) relative to all-medium values (blue line). Estimated annual energy use with all parameters set to low (left) or to high (right) are also shown. Figure 4 shows variability of normalized peak demand for cold climates setting one occupant parameter to high (blue) or to low (red). Estimated peak demand with all parameters set to low (left) or to high (right) are also shown.

OBSERVATIONS

Analysis shows that the elementary school model is sensitive to occupant inputs to approximately the same degree in both cold and warm climates (results for all-high and all-low inputs vary by approximately +65% / -40% from the all-medium case in both climates.) Peak demand is somewhat more sensitive to occupant inputs in cold climates (+25% / -30%) than warm (+/- 20%). Note, in general, the sensitivity results are biased towards heating since simulations were run using a nine-month school calendar. In addition, the peak demand patterns may be somewhat a-typical of non-residential buildings, since the medium school day schedule was modeled to end at 3:00pm. When simulations were run using a twelve-month school calendar (with extended hours), estimates for maximum energy use increased by an additional 15% in the warm climate and an additional +24% the in cold climate, while peak demand increased by 2% in the cold climate, but remained approximately the same in the warm climate (although not all cooling loads were met.)

The parameters that had the most impact on total energy use are listed according to importance for both warm and cold climates in Tables 3 and 4.

Table 3: *Energy Usage Sensitivity, Warm Climate*- importance of singular occupant parameter in a warm climate relative to percentage change of predicted energy usage.

Importance	Parameter	Impact
1	Equipment Load (High)	+ 30%
2	Ventilation Rate (High)	+ 21%
3	Equipment Load (Low)	- 15%
4	Infiltration Rate (High)	+ 14%
5	Ventilation Rate (Low)	- 11%

Table 4: *Energy Usage Sensitivity, Cold Climate*- importance of singular occupant parameter in a cold climate relative to percentage change of predicted energy usage.

Importance	Parameter	Impact
1	Infiltration Rate (Low)	+ 40%
2	Ventilation Rate (Low)	+ 32%
3	Occupant Schedule (High)	+ 27%
4	Equipment Load (Low)	+ 23%
5	Equipment Load (High)	+ 16%

Arguably, as is the case with energy modeling itself, the absolute values documented in Table 3 and Table 4 are largely driven by the assumptions used to determine the inputs. The results presented, however, reveal three observable patterns of dependencies for the model results: 1) deviation in occupant behavior from "typical" tends to increase (rather than decrease) predicted energy usage, 2) peak demand (in a 9 month school year) is impacted by occupant inputs more in cold climates than in warm, and 3) overall, the parameters of occupant behavior which individually have the most impact on predicted results are: a) Equipment Load, b) Ventilation Rate, c) Infiltration Rate and d) Occupant Schedule.

While our crude sensitivity analysis did not attempt to characterize the relationships between individual parameters and predicted energy use output, several additional observations were made. Figure 5 illustrates the complex relationship of equipment load to energy consumption in a cold climate where waste heat can reduce the heating load. Figure 6 begins to show the inherent bias of this study regarding several occupant parameters (and energy efficiency in general)- that greater opportunity exists for individual behavior to increase energy usage (opening a window) than decrease it (taping plastic over the window) since the bottom limit may be set (in this case by tight construction) while the top limit may be relatively unconstrained. In other words, the low value for the parameter (.2 ACH/hr) decreases the energy consumption from average (.5 ACH/hr) less that the high value (2 ACH/hr) increases it.

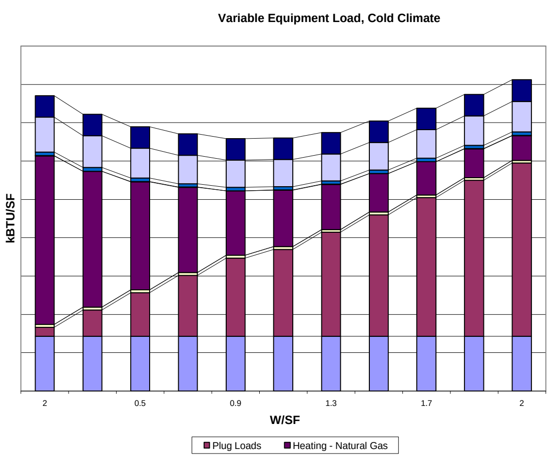

Figure 5

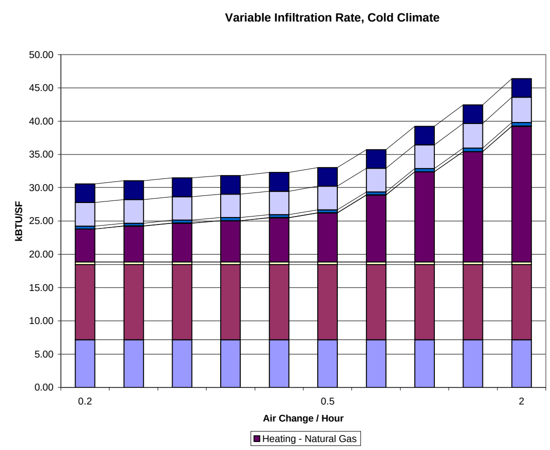

Figure 6

Relationship of occupant behavior parameters to energy use: Figure 5 illustrates the relationship of increased equipment load to energy usage in a cold climate, where waste heat uses electricity but decreases the heating load. Figure 6 demonstrates the bias of occupant behavior to more easily increase infiltration (.5 – 2 ACH/hr) than to decrease it (.5-.2 ACH/hr).

Finally, an important relationship among the parameters is the relationship of schedules and loads. Currently, variability in occupant inputs is defined by assigning different diversity factors over set 24-hour periods using weekday, weekend, and holiday schedules. However, the current relationship is overly simplistic. In the case of equipment and lighting, the diversity factors inaccurately model true operation and performance. For example, in DOE-2, an energy modeler may model electric lights as on at "80% output" for 100% of the assigned hours. In reality, in a building with non-dimmable fixtures, the lights may be on at "100% output" for 80% of the time (and "0%" for the remaining 20%). Although the two scenarios are relatively equivalent in terms of electrical usage, the two different scenarios have larger variability in regard to impact on thermal performance and load shapes.

Similarly modeling pitfalls exist around assigning diversity factors to occupancy schedules. Currently in DOE-2, no building-wide check exists to insure the correct numbers of people are distributed throughout the building at any given time. It remains the responsibility of the modeler to set diversity factors accurately. However, in order to insure the correct numbers of occupants are present at any given hour, it is necessary to multiply all diversity factors by all occupant loads for each space and sum the total occupant count for the building. This is not typically done, and is certainly not checked on an hour-by-hour basis for all occupancy schedules. As a result, it is easy to think that +/- 5% of the building occupants may unintentionally appear or disappear within the energy model for a given hour modeled.

CONCLUSIONS

Occupant behavior is a source of significant uncertainty in energy modeling with predicted energy usage in the elementary school modeled increasing by more than 150% from the lower to the higher values established by experts as representative of "typical" occupant behavior. Variation in a single parameter can significantly impact model results (up to 40% over a run using "all medium" values), and, variation generally results in increased rather than decreased predicted energy use. Relationships and dependencies exist between parameters (loads and schedules) that may further contribute to variability in energy modeling results.

Initially, these conclusions seem to confirm industry sentiment that the relevance of energy models lie in their ability to evaluate alternatives rather than reliably predict energy performance. However, to fully contribute to the design process, these tools must become more reliable and accurate in predicting actual (post-occupancy) building performance. Therefore, a more productive conclusion is to propose that the existing model of the occupant requires improvement. One solution could be to assume that as buildings become more automated, occupant behavior will have less of an impact potential reducing the variability introduced by occupant behavior. However, current trends indicate constructed high performance buildings, many of which have Building Automated Systems (BAS), are also failing to achieve predicted results[3].

This paper is the first step in a detailed investigation of the role of the occupant in energy modeling. We are currently conducting further research to create a more accurate map of the space of energy model sensitivity to occupant model parameters. From this work we hope to gain additional insight and understanding of the current dependencies that exist and have significant impact on model results. We hope to validate our research with occupancy surveys for school districts in California and ultimately improve the overall accuracy of energy modeling through improvements to the model of building

[3] Mark Levi , GSA Building Service, Pacific Rim Region, presentation on US Courthouses, 2005.

occupants. Our intuition is that this may require a new model for the building occupant. At present we are envisioning the creation of various “occupant files” similar to “weather files” which may provide source data for building energy simulations to serve as useful benchmarks in tuning variation of results. In general, further work is necessary and recommended to better understand the impact of the uncertainty introduced by variable occupant behavior on the accuracy of energy modeling results, as well as to identify the overall shortcomings of the current occupant model.

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