EFFECTS OF VARIATIONS OF OCCUPANT BEHAVIOR ON RESIDENTIAL BUILDING NET ZERO ENERGY PERFORMANCE

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ABSTRACT

The objective of the work is to identify the types of occupant-driven residential behaviour variations that most significantly impact a designer's ability to predict energy consumption and peak electrical demand of a house. The study compares the sensitivities of results for a typical house and compares with a house designed to achieve net zero energy consumption, where occupant-driven loads are more influential. The results, generated using EnergyPlus, suggest that cooling setpoints and lighting power have the most influence for a typical house, while plug loads and schedule randomization have more influence over the net zero energy house.

INTRODUCTION

People behave unpredictably. Building science and energy simulation tools have, for the most part, advanced to the extent that they can predict energy usage and demand with accuracy given a set of weather conditions and construction properties. However, social sciences struggle to determine how to forecast what occurs inside of buildings, both commercial and residential. Investigations into the consequences of residential occupant behavioural variations are beneficial.

Previous field studies have measured the impact of occupant-driven parameters (Olofsson et al. 2004, Parker et al. 2002, Pratt et al. 1993, Stoecklein et al. 2000). The results identify large variations in the effect of occupant behaviour among houses in a community and across communities, with corresponding large impacts on energy use.

This paper focuses on the impact of the uncertainty commonly found in occupant-driven energy parameters, such as lighting power, plug loads, thermostat setpoints, occupancy, and natural ventilation. Other bodies of work explore the reasons behind these variations in more detail – this study instead quantifies the impacts of these variations. Computer simulations and uncertainty inputs found in literature are used to quantify the impact of these variations on total energy, electric energy, end-use energy, purchased energy, total peak electric demand, purchased peak electric demand, purchased electric power, and utility peak time purchased power.

This study also explores the effect of improved construction techniques and more efficient space conditioning equipment on the uncertainties found in residential buildings. One could argue that, while tightening residential construction and increasing the efficiency of air conditioners and furnaces does save energy, it may result in a heightened sensitivity to occupant-driven parameters. In the extreme case of a zero energy home with an integrated solar photovoltaic (PV) power system, the effect of occupant behaviour could be even more dramatic.

The objective of this work is to identify the types of occupant-driven residential behaviour variations that most significantly affect a designer's ability to predict whether a typical house, with a given construction, in a given climate can both achieve a ZEH goal and offset utility peak time demand using a 5 kW PV array. Knowing which variables matter most in terms of uncertainty in energy, demand, and coincidence of the house's power draws with utility peak power draws can focus future studies and occupant educational efforts into the areas that will affect the most change.

METHODOLOGY

The approached for this work is based on EnergyPlus simulations of typical residential buildings in the US. The results of the analysis describe the effect of the occupant-driven variables on the building energy performance compared to that of the baseline buildings.

Baseline Buildings

Two different baseline buildings are considered. The "BAB" baseline house is designed to represent a conventional single-family residence. The BAB house design is defined by the Building America Benchmark, a set of criteria published by the Building America program of the U.S. Department of Energy to represent a typical new home built in the US in the mid-1990s (Hendron 2005).

The "PVS" baseline house is designed to represent a very energy efficient single-family residence. The PVS house design is defined to include all energy efficiency measures that are more cost effective for reducing annual energy consumption than the installation of a PV system. The description originates from simulations performed in NREL's

BEopt software, a program that optimizes energy efficiency measures based on energy and product cost data (Christiansen, et al., 2005).

Both typical and energy efficient construction characteristics depend on climate. The two baseline house designs were developed for a prototypical location in Climate Zone 4A (mixed-humid), characterized as having heating degree days HDD_{18} < 3000 °C-days and cooling degree days CDD_{10} < 2500 °C-days. The representative location for the climate zone is Baltimore, Maryland. The building is a two-story, single-family, detached house with an attached garage, an insulated slab-on-grade foundation, unconditioned attic, gas furnace and water heater, and DX air conditioning system. The basic characteristics of the two baseline houses are given in Table 1, which highlights the differences between the two designs.

Table 1 Baseline building descriptions

	BAB	PVS
Conditioned floor area, m^2	167	
Window to wall ratio (all sides)	17.4%	16%
Window distribution	Equal % all sides	40% south
Window U-value ($W/m^2°C$)	3.0	1.7
Window SHGC	0.58	
Wall U-value ($W/m^2°C$)	0.33	0.18
Ceiling U-value ($W/m^2°C$)	0.18	0.11
Number of occupants	3	
Cooling setpoint (°C)	24.4	
Heating setpoint (°C)	21.7	
Furnace AFUE	78%	92.%
Air conditioner SEER	10	18
Major appliance electrical use (kWh/day)	4.91	4.26
Lighting electrical use (kWh/day)	6.15	3.20
Miscellaneous electrical use (kWh/day)	8.23	
Infiltration	Typical	Tight
Water heating	Gas tank	Gas tankless
Ducts, % in conditioned space	35%	100%

The Baltimore location is used for the detailed exploration into the impact of occupant behaviour. Summary analysis is also performed for three other locations (climate zones in parentheses): Chicago (5A cool-humid), Houston (2A hot-humid), and Los Angeles (3B warm-dry). In each climate, the characteristics of the baseline BAB and PVS houses were recalculated to reflect the change in energy codes and HVAC needs in the different climates.

Figure 1 shows the energy consumption characteristics of the BAB baseline houses in the four locations. .

In addition to the two baseline buildings, BAB and PVS, the analysis also explores the impact of occupant-driven variables on the energy performance with the addition of a 5 kW PV system installed on each of the baseline houses. It is assumed that the PV system is grid-tied with a net meter and faces south. The PV system will offset energy purchases for each house, depending on the solar resources at the location. More importantly, the peak electrical demand may not be reduced as much as the net electrical energy consumption.

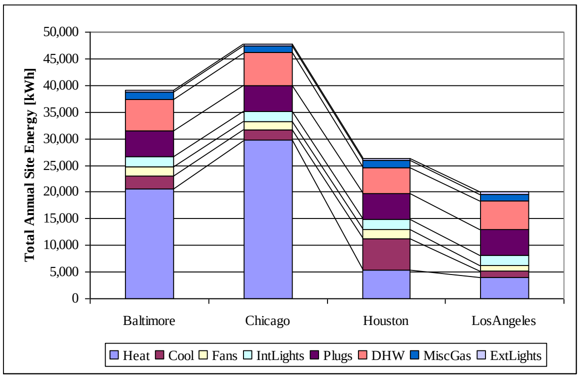

Figure 1 BAB baseline building energy consumption

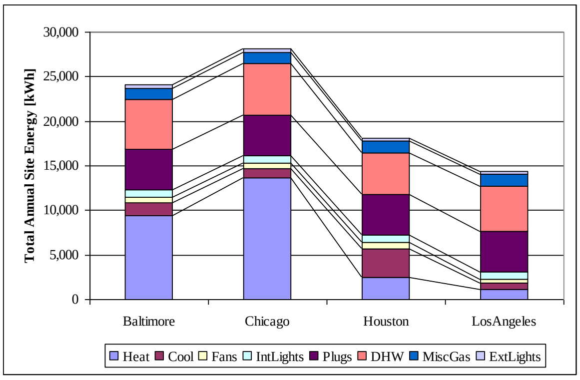

Figure 2 PVS baseline building energy consumption

Strictly speaking, the addition of the PV system does not create a net zero energy house in each location. Rather, the 5 kW system size is kept fixed for each case. The PV system produces between 53% (Houston BAB) and 132% (Los Angeles PVS) of the house annual energy consumption, depending on location and baseline building design.

Occupant Behaviour

Occupant behaviour influences building energy performance through several key variables. The following variables are considered for this analysis:

- heating and cooling setpoints
- window openings for natural ventilation.
- house occupancy level and profile
- lighting power level and profile
- miscellaneous electrical load and profile

Heating and cooling setpoints directly influence the energy consumption of the HVAC equipment and the impact is expected to be influenced by the energy efficiency of the house. Window openings for natural ventilation influence cooling energy consumption during mild weather. Miscellaneous electrical loads (MELs) include the various small appliances around the house, but do not include loads due to large appliances such as refrigerators. Lighting and MELs have both a direct effect on the electrical energy consumption and an indirect effect on the HVAC needs of the building through the heat generated by the loads. Occupants also generate heat that affect HVAC consumption, independent of their influence on lighting and MELs.

The impact of the heating and cooling setpoints is examined by simply changing their values over a typical range. The impact of natural ventilation is examined by changing the probability that windows will be open when the house needs cooling and the outdoor conditions are favourable for meeting the cooling load.

The impact of the occupancy, lighting, and MEL variables are examined by changing both the magnitudes and schedules. The magnitude effects are explored by uniformly increasing and decreasing the loads throughout the year, relative to the magnitudes given in Table 1. In addition, the load profiles, or schedules, for the variables are systematically changed over the course of the day and year. Unfortunately, the literatures shows that the magnitude and schedule of these variables vary dramatically among households – it is not uncommon to see standard deviations of distributions among households as high as 25%, 50%, even 100%, of the mean. In general, the work presented here examined scaling factors in the range of 75% to 250% of the baseline values.

In the baseline buildings, these variables are assumed to have the same hourly schedule every day of the year. The schedules are shown in Figure 3.

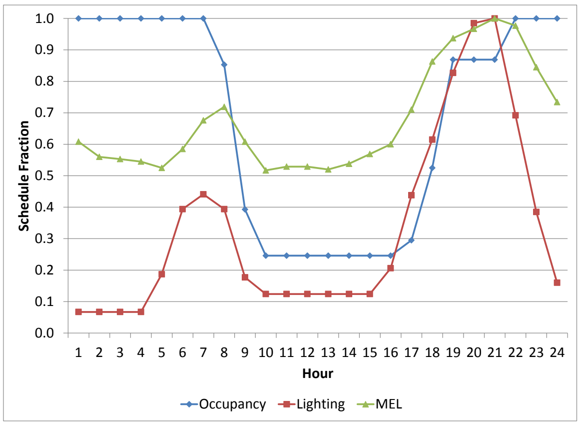

Figure 3 Baseline building load schedules

The impact of schedules is examined by both systematically changing the shape of the daily schedules and by imposing random variation to the hourly values over the course of the year. Four alternative daily schedules are examined here.

- The “Inverse” schedule mirrors the baseline schedule about noon.
- The “Flat” schedule has no hourly variation.
- The “More Smooth” schedule keeps the same basic daily profile shape, but reduces the difference between the minimum and maximum values.
- The “Less Smooth” schedule keeps the same basic daily profile shape, but increases the difference between the minimum and maximum values.

For the Flat, More Smooth, and Less Smooth schedules, the magnitude of the peak is scaled to ensure that daily average value is the same as the baseline schedule. Figure 4 shows the five different daily schedules for lighting, normalized such that the daily average value for each schedule is unity. Similar schedules have been developed for MELs and occupancy.

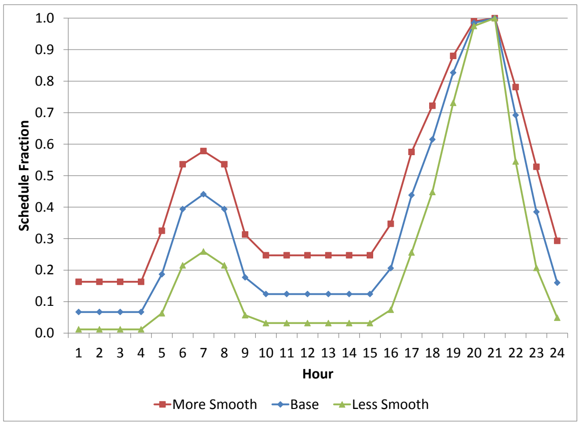

Figure 4 Schedule variations for lighting

Real schedules for lighting, MELs, and occupancy are not the same every day of the year, but exhibit variations that reflect the vagaries of human behavior. The approach used in this study to account for these hour-to-hour variations is relatively simplistic and follows the method used in the HOMER software (Lilienthal and Lambert 1997). At each hour, a perturbation factor α_i is calculated based on normally distributed values of hourly and daily variations in the profile values.

$$\alpha_i = 1 + \delta_{daily,j(i)} + \delta_{hourly,i} \quad (1)$$

The values of $\delta_{hourly,i}$ are 8760 hourly values calculated as a random number from a normal distribution with a given standard deviation. The values of $\delta_{daily,j(i)}$ are 365 daily values calculated as random numbers from a normal distribution with a given standard deviation. For this analysis, the standard deviations of the hourly and daily profiles, σ_{hourly} and σ_{daily}, respectively, are expressed as percentage of the mean value and ranged from 0% to 50%.

RESULTS AND DISCUSSION

The results of the analysis are based on the effect of the occupant-driven variables on the building energy performance compared to that of the baseline buildings. For this analysis, energy performance is characterized using several metrics:

- Annual site energy consumption (kWh)
- Annual electrical energy consumption (kWh)
- Electrical demand (kW)
- Coincident electrical demand (kW)
- Purchased annual electrical energy (kWh)
- Purchased electrical demand (kW)
- Purchased coincident electrical demand (kW)

For this paper, all energy is expressed as site energy. The electrical demand is calculated as the peak electrical power in a 15-minute period during the year. The coincident demand is the peak electrical power in a 15-minute period between 3:00 – 6:00 pm during the months of June through September. The purchased energy and demand results represent the electricity that must be purchased from the utility company when the house has a 5 kW grid-tied PV system. The purchased energy includes all electrical energy that is delivered to the house when the house PV system cannot meet the load.

The results are presented first for the BAB and PVS houses in Baltimore.

Energy Sensitivity

It is well known that changing heating and cooling setpoints affect building energy use. Similarly, changes to levels of lighting, MELs, and occupancy, and the ability to open windows for appropriate natural ventilation, affect energy consumption in predictable ways.

As an example of this effect, Figure 5 shows the effect of increasing the MEL compared to the values for both the BAB and PVS baseline houses in Baltimore. The figure shows the change in total and electrical energy use versus the increase in peak daily MEL power, using the profiles given in Figure 3, compared to the baseline building. For reference, the MEL power for both baseline buildings is 508 W.

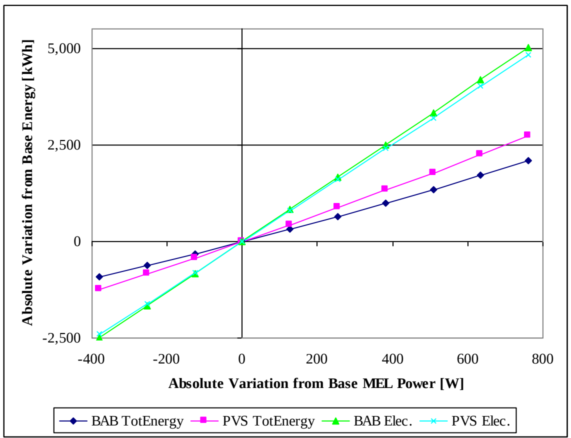

Figure 5 Sensitivity of total and electrical energy to MEL power

The results show that the changes in annual total site energy and annual electrical site energy use are linear with MEL power (and correspondingly, MEL energy). Close inspection reveals a very slight nonlinearity, due to the interactions between MELs and HVAC energy consumption, but the curves are linear with coefficients of determination (R^2) greater than 98%.

Table 2 Energy sensitivity to occupant variables

	BAB	PVS
% change in electrical energy per % change in lighting energy	0.19	0.11
% change in electrical energy per % change in MEL energy	0.30	0.41
% change in total energy per change in number of occupants	0.8 % per person	1.1% per person
% change in electrical energy per °C change in cooling setpoint	-6.2	-4.3
% change in total energy per °C change in heating setpoint	6.5	5.4

The heating setpoint has an expected change on total energy use; the effect on electrical energy use is very small, due only to changes in supply fan energy consumption.

The probability that windows would be open at times of beneficial natural ventilation had a very small effect on electrical energy use in Baltimore. Probabilities ranging from 0% to 100% changed total energy consumption less than 1% and electrical energy consumption by less than 3%.

The results show very little impact of the number of occupants. However, it must be noted that these results only account for the *direct* impact due to the heat and moisture generated by the occupants. While additional occupants would also be expected to use more lighting and more MELs, these effects are not included here.

The hourly variation, or schedules, in interior lighting, MELs, and number of occupants would not be expected to change significantly as long as the daily average value remained constant. The results of the analysis confirm this expectation. Changes in load schedules among Base, Inverse, Flat, More Smooth, and Less Smooth showed difference of less the 0.5% in total annual energy use and less than 1% in electrical energy consumption. The slight difference reflect that, during the swing seasons and much of the cooling season, many hours of the day do not require heating or cooling; changes in schedules can have an impact at these marginal times.

Similar energy performance results are obtained when examining the impact of random fluctuations, or noise, in the hourly profiles for the lighting, MELs, and number of occupants. The effects can become more noticeable at very high standard deviations for the hourly and daily profiles.

Electrical Demand Sensitivity

While the effect of occupancy-driven variables on building energy use is readily understood and expected, the effect on peak electrical demand is less obvious. Part of the uncertainty arises from the uniqueness of the demand as typically defined – the single greatest power draw during a year over a 15-minute period. In this case, the effect of hourly variations in loads can have a significant effect. For this discussion, we will focus only on electrical demand, which typically occurs in the cooling season. For reference, Table 3 shows the peak electrical demand in each month for the baseline BAB and PVS houses in Baltimore. Winter demand in the PVS house is smaller due to the reduced appliance and lighting energy use, which also reduces the peak, and the smaller indoor fan for the furnace. Demand is more significantly reduced in summer months due to the lower cooling loads in AC efficiency. On an annual basis, the electrical demand of the PVS house is 41% less than the BAB house and both occur at the height of summer at a time of maximum cooling needs.

Table 3 Baseline monthly electrical demand (kW)

	BAB	**PVS**
January	2.03	1.32
February	2.03	1.32
March	1.89	1.26
April	1.92	1.29
May	1.82	1.19
June	4.14	2.43
July	4.37	2.56
August	4.10	2.42
September	4.07	2.41
October	1.88	1.22
November	1.84	1.26
December	2.00	1.31
Annual	**4.37**	**2.56**

Of the occupant-driven variables discussed above, only the cooling setpoint, lighting level and schedule, and MEL level and schedule have a significant impact on electrical demand. Heating setpoint does not affect electrical use in the summer, the opportunity for natural ventilation only occurs during mild weather, and the direct effect of heat gains from the number of occupants is small.

The impact of the cooling setpoint is clearly to increase electical demand with lower setpoints. In general, the electrical demand increases 5.1% and 4.2% per degree Celcius decrease in cooling setpoint for the BAB and PVS houses, respectively. Nonlinear affects appear for changes greater than approximately ±2°C from the baseline setpoint of 24.4 °C.

The impact of increases in lighting energy use over the baseline is also to increase electrical demand. At the time of peak demand, in the summer during peak cooling times, the increases in lighting also increase cooling loads. In general, the results show that the relative increase in electrical demand for the BAB and PVS houses is 14% and 8% of the relative increase in peak lighting power, respectively. Note that this analysis assumes that the lighting power is scaled at all hours of the year and that a percentage increase in lighting power is also the same relative increase in lighting energy use. In other words, for the BAB house, a 10% increase in lighting use results in a 1.4% increase in electrical demand.

MELs show similar impact on electrical demand as lighting. In general, the results show that the relative increase in electrical demand for the BAB and PVS houses is 13% and 20% of the relative increase in peak MEL power, respectively.

While the hourly variations, or schedules, in lighting and MELs did not show significant impact on annual energy consumption, the schedules can have a more significant effect on electrical demand. Table 4 shows the effect of the five different schedules described above on the electrical demand of the BAB and PVS houses. The results show changes in peak demand of 10%-13% based only on shape of the schedules.

Table 4 Effect of hourly load shape on electrical demand (kW)

	BAB	**PVS**
Base	4.37	2.56
Flat	3.94	2.31
Inverse	3.99	2.33
More Smooth	4.13	2.41
Less Smooth	4.85	2.89

The Less Smooth schedule, which includes several smaller values punctuated by a few large hourly value, exhibits the most obvious change – a substantial increase in peak demand. Each of the other schedules causes a decrease in peak demand because their hourly peaks are smaller than, rather than larger than, that of the Base load shape. Of these three other shapes, the Flat shows the most sizeable decrease in peak demand, but this shape does not likely represent reality as much as the other schedules.

Similar demand results are obtained when examining the impact of random fluctuations, or noise, in the hourly profiles for the lighting and MELs. Table 5 shows the results for the base schedule, with every day the same schedules as given in Figure 3, and two alternatives with different random perturbations applied to the hourly schedules. One schedule uses has a distribution of hourly variations with a standard deviation of 25% of the mean and a distribution of daily variations with a standard deviation of 20% of the mean. The second alternative schedule uses hourly and daily standard deviations of 50% and 50%, respectively.

The results indicate that random perturbations to the nominal schedules always increase the peak demand and the PVS house is relatively more sensitive to the perturbations. While these results describe the annual peak demand, which focuses on the peak summer times, monthly demand is similarly affected throughout the year.

Table 5 Effect of random schedule noise on electrical demand (kW)

Noise Level (%Hourly / %Daily)	**BAB**	**PVS**
Base	4.37	2.56
25% / 20%	4.80	2.99
50% / 50%	5.58	3.52

Figure 6 illustrates the reason of for the differences by showing a histogram of the occurrence of particular electrical demand values for the PVS house. The figure shows the Base (no-noise) house having a higher peak occurrence frequencies, but a narrower range of demand bins represented. The random schedule noise basically spreads out the distribution more evenly by increasing the probability of under-represented bins being chosen and vice versa. The higher noise level significantly magnifies this effect.

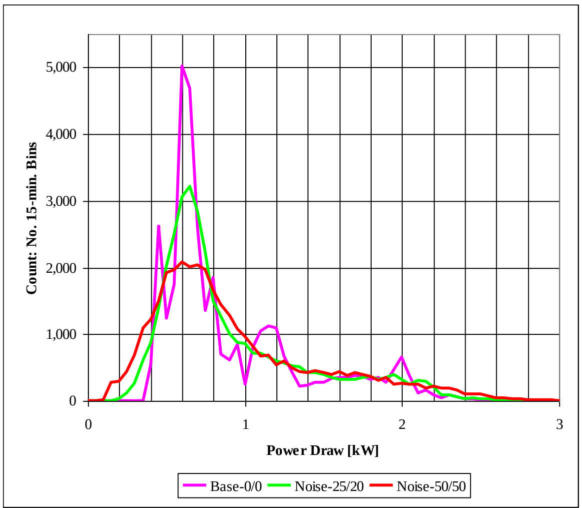

Figure 6 Histogram of PVS normalized power

PV System Results

All previous results in this section describe the effect on energy and demand assuming that all energy and power is provided by utility companies. Different effects are observed when the BAB and PVS houses in Baltimore are equipped with a 5 kW grid-tied PV system. In these cases, the energy and demand of interest are those purchased from the utility company, offset from the overall values by the effects of solar collection. A 5 kW system in Baltimore will produce 97% of the annual energy use for the PVS building over the course of the year, making the system nearly a net zero energy building. However, on an hourly basis the system produces more power than it can use much of the year and must draw power from the electrical grid during hours when the PV output is less than the building electrical load, including all nighttime hours.

Given the nature of solar resources and overall building electrical load profiles, there are significant hours when the PV system can not meet the building electrical load, even in the summer. Building loads are typically shifted toward the early evening hours, when lighting and appliance electrical use is high, and the when the peak cooling load occurs. These daily peaks typically occur near 5:00 pm, well past the peak of PV system production. As a result of these factors, increases in lighting and MEL use, decreases in cooling setpoint, and schedule variations that shift more loads away from mid-day all tend to increase the electrical demand and the energy that must be drawn from the utility grid.

An example if the impact of these effects on the purchased demand is shown in Table 6. The table gives the impact of schedule and random fluctuations on the purchased demand for the BAB and PVS houses in Baltimore. The total electrical demand for the same comparisons are shown in Table 4 and Table 5. By comparing the tables, it is observed that the purchased demand is always less than the absolute peak demand. However, the purchased demand is only slightly less than the actual peak, and the effect of occupant-driven variables is very similar. The installation of the 5 kW PV system has had little effect.

Table 6 Effect of schedules on purchased electrical demand (kW)

	BAB	**PVS**
Base	4.32	2.54
Flat	3.76	2.23
Inverse	3.71	2.12
More Smooth	4.08	2.38
Less Smooth	4.82	2.89
25% / 20% noise	4.74	2.96
50% / 50% noise	5.50	3.50

Often a monthly or annual peak demand number does not entirely represent the hourly changes experienced during the annual simulations. For instance, a sharp increase in peak demand may not represent an increase in the majority of demand values – it could instead act as an outlier. An electric utility benefits from understanding the ranges of power draws it needs to accommodate during its peak hours, which generally occur between 3:00 – 6:00 pm during summer months. To show the range of power needed at each 15-minute timestep Figure 7 and Figure 8 show the cumulative histograms of the purchased power draws from the BAB and PVS houses, respectively. The power values are normalized to the peak Base purchased power value. All data points in the figures represent purchased power draws during the utility peak time only, from 3:00 – 6:00 pm from June through September.

Regardless of load shape, the figures demonstrate that the PVS house experiences far more zero-purchased-demand hours during the utility peak than does the BAB house. This finding is intuitive since both houses use a 5kW PV array, yet the PVS house requires less power because of its tight envelope and efficient appliances and systems. The extent of the discrepancy between the two house types would be less obvious without the data shown in the cumulative histograms. The BAB house draws zero utility power during only 8-15% of utility peak hours, yet the PVS house draws zero utility power during 35-42% of utility peak hours. Furthermore, during 50% of the utility peak hours, while the BAB house purchases power at 35% or less of its peak value, the PVS house purchases power at 10-15% or less of its peak value. Clearly, a house's construction, appliances, and systems can have a substantial effect on the ability of its PV system to relieve an electric utility's power requirements during peak hours.

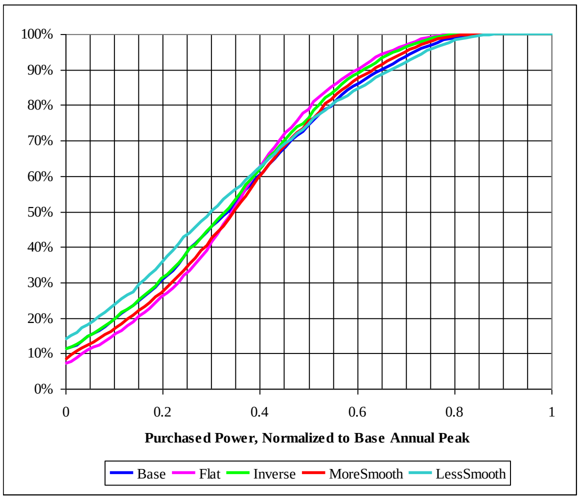

Figure 7 Cumulative Histograms of BAB Normalized Purchased Power Occurring During Utility Peak

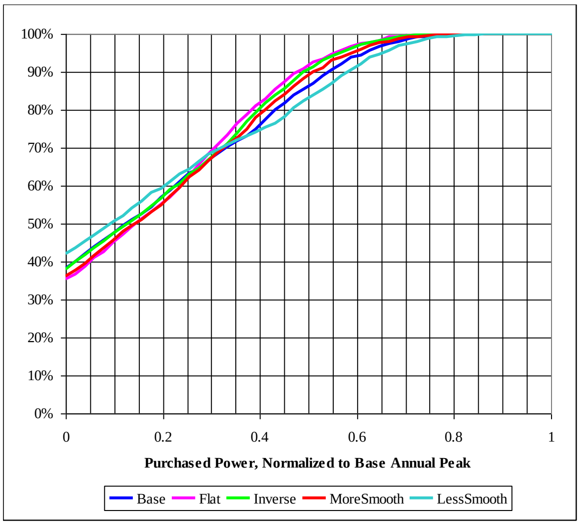

Figure 8 Cumulative Histograms of PVS Normalized Purchased Power Occurring During Utility Peak

Effect of Climate

So far, all results have been for houses located in a single location, Baltimore. It is expected that climate could affect the impact of occupant-driven variables. A similar analysis has been performed for Chicago, Houston, and Los Angeles.

The analysis of energy consumption results in different locations showt that the general trends for Baltimore apply in other locations. Similarly, the general trends for electrical demand also apply broadly to the other locations.

Among the more interesting results in different climates are the effects of schedule profile shape on electrical demand. Figure 9 shows that schedule noise has significant impact on purchased peak demand across all climate zones.

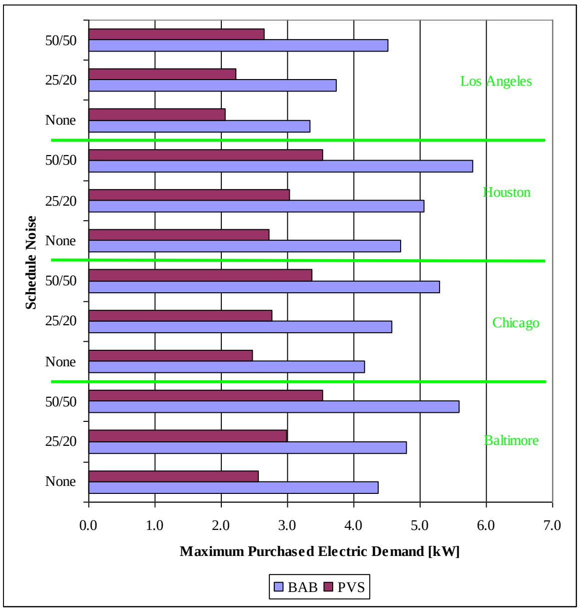

Figure 9 Sensitivity of total electrical demand to schedule noise

CONCLUSIONS

The analysis underlying the results shown here has produced myriad findings about how BAB and PVS residences in Blatimore, Chicago, Houston, and Los Angeles react to the scaling of each of six occupant-driven variables, as well as to the daily and hourly variations in schedules. However, we now return to the original objective – to identify, for a given house type and climate, which occupant-driven parameters most significnatly affect the ability to achieve zero energy goal and to offset utility peak power needs.

The results of the analysis indicate that the heating setpoint, the number of occupants, and the probability of opening windows for natural ventilation have little effect on purchased energy or purchased demand, regardless of the studied house types or locations.

The remaining five variables do have significant influence on the ability of offset utility energy and demand. Table 7 shows the ranking of these five variables by house type and location. The ranking reflects the influence of uncertainty in the variable on the energy performance and is weighted to the effect on purchased peak power. The table also lists the maximum percentage change in purchased demand observed in the study.

It is interesting to note that, while cooling setpoint ranks most highly for the conventional BAB house, random fluctuations in the schedules and the level of miscellaneous electrical loads rank highest in influence for the energy efficienty PVS house. The rise in importance of these variables shows that, once a builder has optimized the envelope and building systems, the unpredictable loads generated by the occupants gain greater influence than in a house whose envelope-driven loads dominate the consumption profile.

Table 7 Ranking of occupant-driven parameter by ability to offset utility energy and demand (max change in purchased demand)

	BAB Houses			
Rank	**Baltimore**	**Chicago**	**Houston**	**LA**
1	Cool Set (35%)	Cool Set (34%)	Cool Set (28%)	Noise (36%)
2	Lighting (28%)	Lighting (27%)	Lighting (26%)	Lighting (30%)
3	MELs (23%)	Noise (27%)	MELs (21%)	MELs (27%)
4	Noise (28%)	MELs (22%)	Noise (21%)	Cool Set (15%)
5	Schedule (14%)	Schedule (14%)	Schedule (13%)	Schedule (15%)
	PVS Houses			
Rank	**Baltimore**	**Chicago**	**Houston**	**LA**
1	Noise (39%)	MELs (37%)	MELs (33%)	MELs (39%)
2	MELs (35%)	Noise (28%)	Noise (26%)	Noise (30%)
3	Cool Set (24%)	Lighting (20%)	Cool Set (18%)	Lighting (20%)
4	Lighting (20%)	Cool Set (20%)	Lighting (18%)	Cool Set (15%)
5	Schedule (16%)	Schedule (16%)	Schedule (15%)	Schedule (15%)

REFERENCES

Christensen, C., S. Horowitz, T. Givler, A. Courtney, G. Barker. 2005. BEopt: Software for Identifying Optimal Building Designs on the Path to Zero Net Energy. Proceedings ISES 2005 Solar World Congress, Orlando, FL.

Hendron, R. 2005. NREL Building America Research Benchmark Definition, Updated December 29, 2004. Golden, CO.

Lilienthal, Peter and Lambert, Tom. HOMER: The Hybrid Optimization Model For Electric Renewables. Program and additional information available at the NREL website: http://www.nrel.gov/homer, 1997.

Olofsson,T., A. Meier, and R. Lamberts. 2004. Rating the Energy Performance of Buildings. *The International Journal of Low Energy and SustainableBuildings*, Vol. 3.

Parker, D.S. 2002. Research Highlights from a Large Scale Residential Monitoring Study in a Hot Climate. Proceedings from International Symposium on Highly Efficient Use of Energy and Reduction of its Environmental Impact, Japan. pp.108-116. 2002.

Pratt, R.G., C.C. Conner, B.A. Cooke and E.E. Richman. 1993. Metered End-use Consumption and Load Shapes from the ELCAP Residential Sample of Existing Homes in the Pacific Northwest. *Energy and Buildings*, v.19, pp. 179-193. 1993.

Stoecklein, A., Pollard, A., Tries, J., Camilleri, M., Isaacs, N., and Fitzgerald, G. 2000. Understanding Energy End-Use in New Zealand Houses. ACEEE Summer Study 2000, Monterey, USA.