Accounting for the Occupancy Variable in Inverse Building Energy Baselining Models

Bass Abushakra
Environmental Energy Technologies Division
Lawrence Berkeley National Laboratory
Berkeley, CA

David Claridge
Energy Systems Laboratory
Texas A&M University
College Station, TX

Abstract

The occupancy factor is often underestimated in inverse modeling of building energy use, or accounted for by grouping the daily data in occupied and unoccupied groups which are modeled separately. For instance, in institutional buildings it is common to identify "weekdays/weekends", "semester breaks", and "holidays" daytypes. In order to develop one model that accounts for all periods, i.e., occupied and unoccupied, at an hourly time scale, a dummy variable (regressor) can be used. The dummy variable is often used in a simplified way; for instance, having a value of 0 between 8:00 AM and 5:00 PM, and 1 between 5:00 PM and 8:00 AM, for an office building. In this paper, the effect of using different alternatives in accounting for the occupancy variable in inverse modeling of building energy use is investigated, and the resulting uncertainty in the predictions, using the SMLP inverse method are presented.

Introduction

To perform the evaluation of different alternatives in accounting for occupancy in inverse models of building energy use, five different options were used, basically fractions between 0 and 1; listed from the most elaborated to the simplest option: (1) based on a walk-through survey of the building, used as the standard for comparing the other surrogates for occupancy, (2) surrogate occupancy derived from lighting and equipment load profiles (procedure described below), (3) simply derived from the lighting and equipment loads by dividing all values by the absolute maximum value of lighting and equipment consumption, (4) a value of 1 during weekdays occupied hours; 0 during unoccupied hours; 0.33 during weekends for the same business hours, and 0 outside business hours, and (5) a value of 1 for weekdays and 0 for weekends.

The study was performed using synthetic data from a calibrated DOE-2 simulation of a large institutional building (Engineering Center), using an occupancy profile based on a walk-through survey, and run with Miami (FL) TMY weather conditions, representing the hot and humid climate zone in the United States (Abushakra 2001). The study was conducted using the cooling energy use with a dual duct constant air volume (DDCAV) and a dual duct variable air volume (DDVAV) systems, which resulted in a total of 10 cases (2 HVAC systems x 5 occupancy options). Synthetic data from a calibrated simulation was used in the analysis to illustrate using a survey of building occupancy as a target alternative and how other simplified alternatives would perform, comparatively. Thus the occupancy profile based on the walk-through survey was considered the “true” or “actual” occupancy for this test.

Previous work on occupancy

Very little published work has dealt with the occupancy factor as a variable in building energy use. In the forward modeling approach such as DOE-2 (DOE 1981) and BLAST (U.S.Army 1979), the total number of people occupying the building is estimated, and then multiplied by a diversity factor profile. ASHRAE Standard 90.1 (ASHRAE 1989) includes a typical occupancy profile for office buildings, where three daytypes are considered: (1) weekday, (2) Saturday, and (3) Sunday.

Keith and Krarti (1999) summarized a methodology used to develop a simplified prediction tool to estimate peak occupancy rate from readily available information, specifically average occupancy rate and number of rooms within an office building. The study was carried out in a laboratory campus with three similar two- and three-story buildings in Boulder, CO, comprising approximately 1200 rooms, with 1174 having individual occupancy sensors. A total of 195 sensors were selected, and the raw data included each room's status as either "occupied" or "unoccupied", and an associated time/date stamp taken from the central facility management computer, at nominal 15-minute intervals, for a 12-month period. The average occupancy rate was defined as the average over a period of one month, for either the entire nine-hour workday period (8:00 AM to 5:00 PM) or for each hour separately. Calculations were performed with every five-minute period within the daily period of interest over the month, counting the occupied and unoccupied records for all the rooms in the specified set. The average occupancy rate is equal to the number of occupied records divided by the number of both occupied and unoccupied records. The average hourly occupancy is the monthly average of the occupancy rate in that particular hour of all workdays. Therefore for any given set of rooms, there are nine average hourly occupancy rates associated with each month. To determine the peak occupancy rate, numerous combinations of linear terms were evaluated, starting with just the two independent variables of average occupancy rate and number of rooms, and increasing the number and variety of terms to develop the best fit. A multiple linear regression model of peak occupancy rate was finally developed which is a function of average occupancy rate, number of rooms, and other variables that are combinations of these two variables. Predicting the peak occupancy rate can help in determining potential savings due to occupancy-sensing lighting controls, in order to avoid errors in predicting the effect on peak demand. The work shows the derived average and peak typical occupancy profiles for the case study office building. However, the results are based on measurements conducted in one site only. Although few such efforts of monitoring the occupancy variable with different techniques exist, acquiring such data on a large scale is not an easy task, and therefore calculating a surrogate occupancy variable is feasible and important.

Camden (1999) has also accounted for the effect of the change in occupancy on the calculation of energy savings from retrofits, and proposed to recalculate (calibrate) the energy consumption baselines of buildings experiencing change in occupancy. The author established linear and logarithmic correlation models between the whole building electricity consumption and demand, and the occupancy density (person/1000ft^2).

In the following, a novel approach to create a surrogate occupancy variable from the lighting and equipment load profiles is developed and tested.

Novel approach to derive a surrogate occupancy variable

The typical average and peak occupancy load shapes developed by Keith and Krarti (1999) required extensive monitoring of occupancy for a 12-month period. This procedure is not feasible to be carried out every time the occupancy profile in a specific building is sought. Therefore an accurate surrogate occupancy variable that can be derived in a simple fashion in order to produce typical occupancy load shapes should be developed.

To derive a surrogate occupancy variable, lighting and equipment load schedules (diversity factors) were investigated. These lighting and equipment diversity factors were determined by a previous study (Bronson 1992) for the Engineering Center at Texas A&M University based on the daytyping method of Katipamula and Haberl (1991), and the ELF/OLF technique developed by Haberl and Komor (1990). The data used to determine these schedules (diversity factors) was monitored by the Energy Systems Laboratory at Texas A&M University. Bronson (1992) generated occupancy profiles for 12 different zones of the case-study building, for the determined daytypes, based on a walk-through survey of the building. For this study, an average occupancy profile was derived, for each daytype, from the 12 different profiles used by Bronson (1992). The average profiles are shown in Figure 1. Figure 2 shows the typical load shapes for lighting and equipment for the specified daytypes.

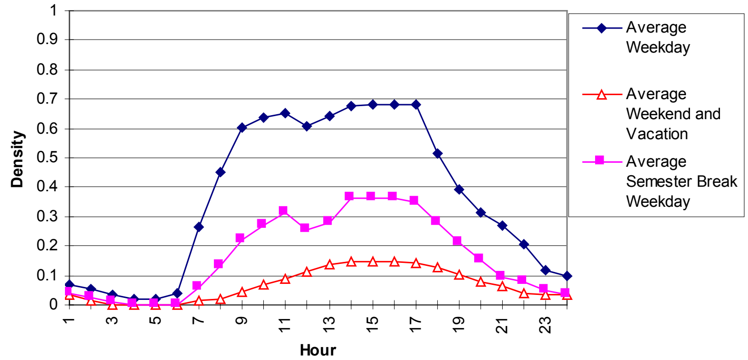

Figure 1 Average occupancy profiles derived from a walk-through survey in the Engineering Center (Bronson 1992)

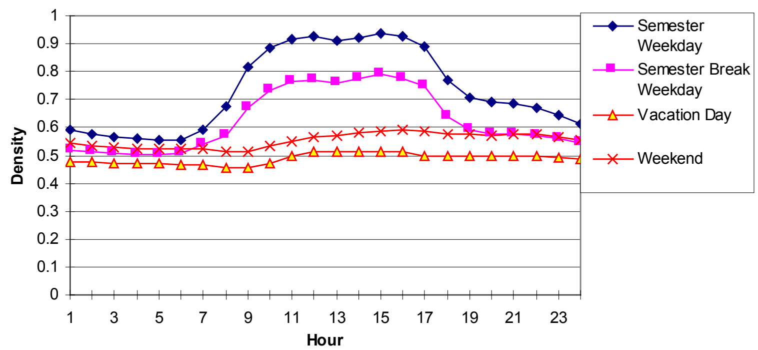

Figure 2 Average typical load shapes of lighting and equipment loads in the Engineering Center (Bronson 1992).

After examining the occupancy and the lighting and equipment profiles and analyzing the data, a strong correlation was found between the occupancy and the lighting and equipment variables through a linear regression analysis, as one would intuitively expect. The details of the linear regression analysis are covered below.

For the weekdays daytype, the following model was obtained, with $R^2 = 0.9267$,

$$OCCUP = 1.721\ LTEQ - 0.8976 \quad (1)$$

For the weekends and vacations daytype, the following model was obtained, with $R^2 = 0.6958$,

$$OCCUP = 2.0309\ LTEQ - 0.9909 \quad (2)$$

For the semester breaks weekdays daytype, the following model was obtained, with $R^2 = 0.9143$,

$$OCCUP = 1.1942\ LTEQ - 0.5826 \quad (3)$$

Figures 3 to 8 show the regression-derived surrogate occupancy profiles as compared with the profile generated with the walk-through survey. The results of the simple linear regression of the occupancy variable against the lighting and equipment load shapes produced profiles reasonably similar to the occupancy profiles obtained by a walk-through survey, which shows the strong correlation between them.

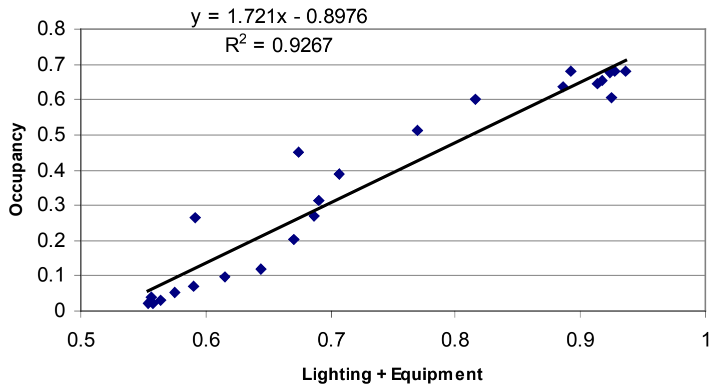

Figure 3 Linear regression of occupancy as a function of lighting and equipment for the weekdays daytype.

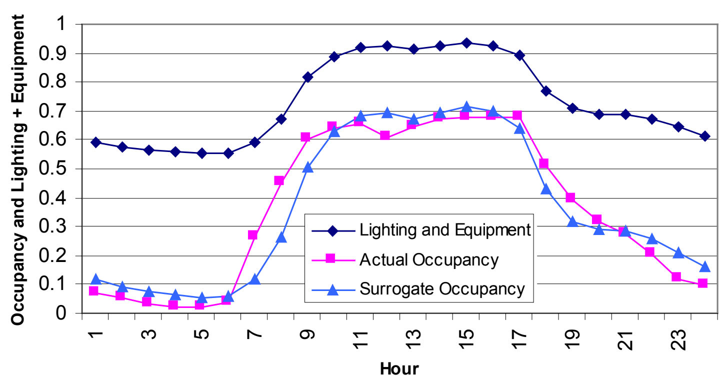

Figure 4 Regression-derived surrogate occupancy profile for the weekdays daytype.

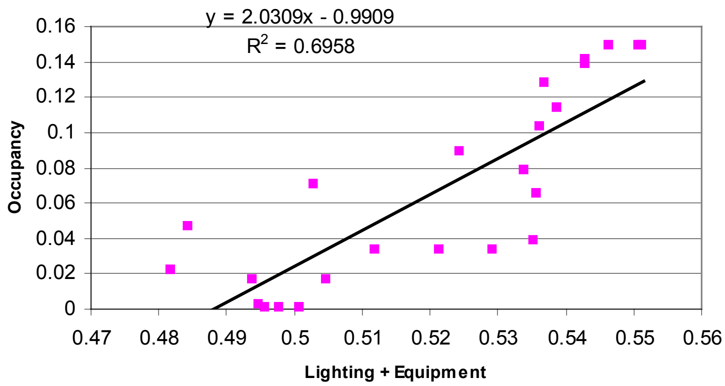

Figure 5 Linear regression of occupancy as a function of lighting and equipment for the weekends/vacations daytype.

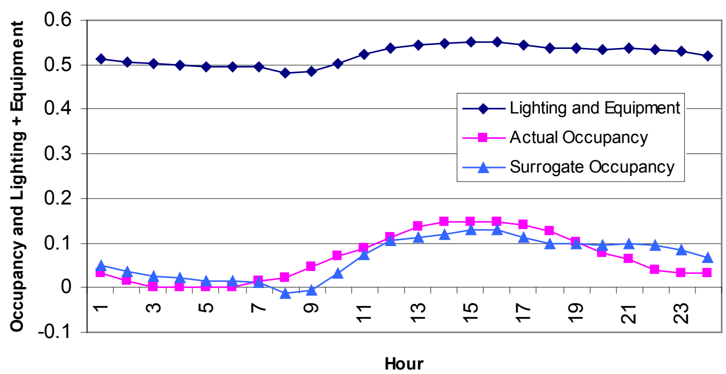

Figure 6 Regression-derived surrogate occupancy profile for the weekends/vacations daytype.

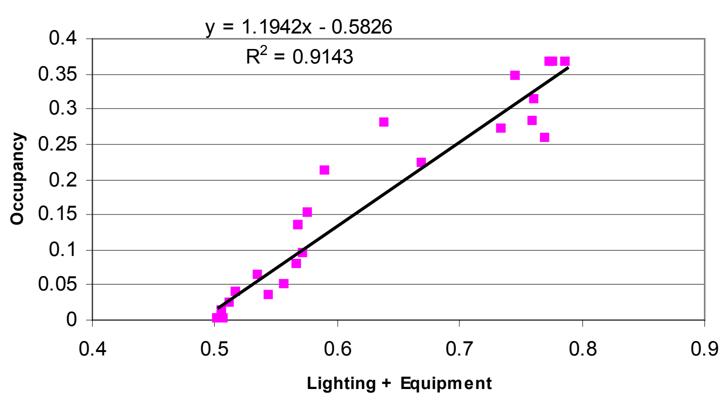

Figure 7 Linear regression of occupancy as a function of lighting and equipment for the semester breaks weekdays daytype.

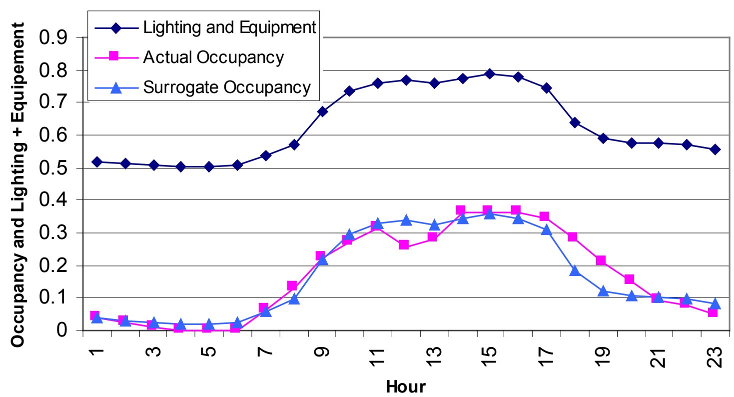

Figure 8 Regression-derived surrogate occupancy profile for the semester breaks weekdays daytype.

This strong correlation lead to establishing a relationship between these two variables; the occupancy, and the lighting and equipment. The proposed function, which is a *linear transformation* of the lighting and equipment data, provides a *surrogate occupancy* variable, as follows:

$$OCCUP = OCCUP_{Max}\left(\frac{LTEQ - LTEQ_{Min}}{LTEQ_{Max} - LTEQ_{Min}}\right) \quad (4)$$

where: $OCCUP$ = hourly occupancy density (fraction of 1)
$OCCUP_{Max}$ = maximum hourly occupancy density
$LTEQ$ = hourly lighting and equipment load density
$LTEQ_{Min}$ = minimum hourly lighting and equipment load density
$LTEQ_{Max}$ = maximum hourly lighting and equipment load density

In Eq. (4), the maximum occupancy ($OCCUP_{Max}$) can assume any value, for instance, *1*, *0.7*, or even *1000* (for example, if the total number of occupants is to be used, instead of diversity factors), and can never result in a negative value as with the linear regression models shown above (weekends/vacations profile).

This simple manipulation of the lighting and equipment typical load shapes, which reflects the strong correlation between the occupancy and the lighting and equipment loads, produced profiles reasonably similar to the occupancy profiles obtained by the walk-through survey, which suggests accepting the results of a surrogate variable for the true occupancy variable. Physically, the data manipulation is explained by the fact that the lighting and equipment load is strongly correlated (and in fact driven) by the occupants, with the difference of having some lights and equipment left "ON" during the unoccupied hours. Figures 9, 10, and 11 show the linear-transformation-surrogate occupancy profiles as compared with the profiles generated with the walk-through survey.

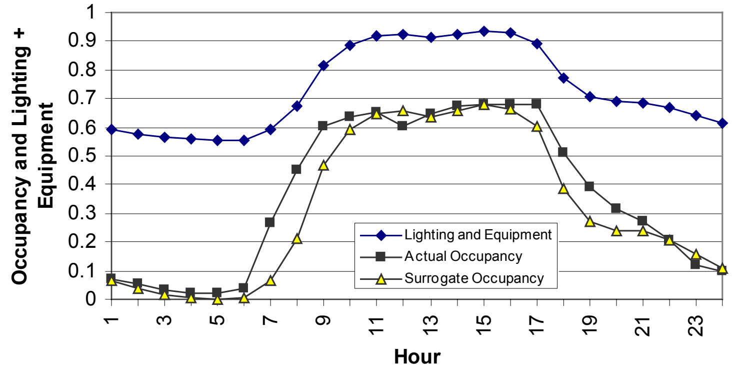

Figure 9 Linear-transformation-surrogate occupancy profile for the weekdays daytype.

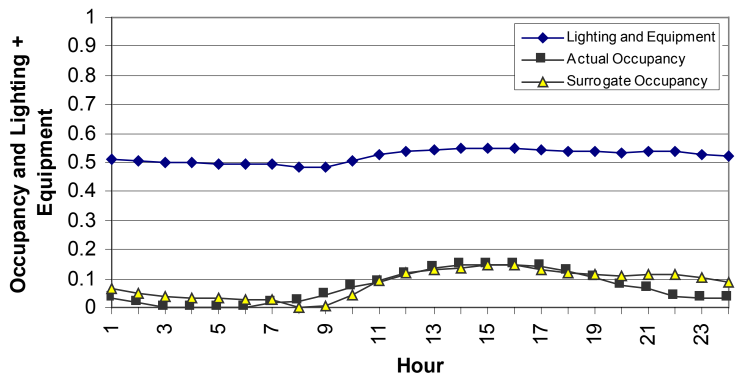

Figure 10 Linear-transformation-surrogate occupancy profile for the weekends/vacations daytype.

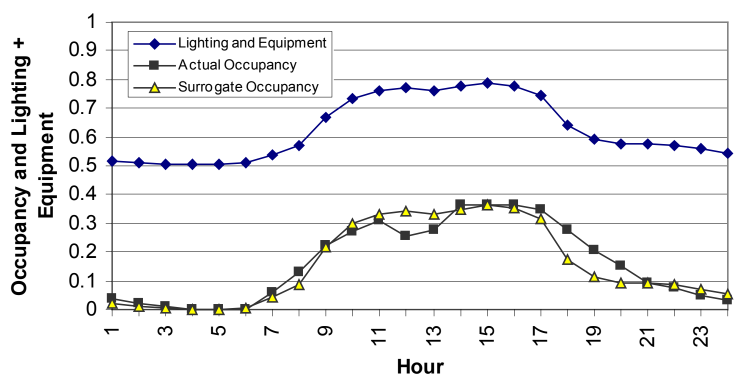

Figure 11 Linear-transformation-surrogate occupancy profile for the semester breaks weekdays daytype.

Results of the occupancy study

The evaluation of the effect of different methods to account for occupancy factor in the inverse modeling, mainly the multiple linear regression modeling, is evaluated through the consideration of five different options used with the SMLP method (Abushakra 1999). The SMLP method (Short-term Monitoring Long-term Prediction) uses a multiple linear regression of the energy use as a function of the outdoor dry bulb temperature, outdoor specific humidity, lighting and receptacles use, and occupancy, based on a two-week period of hourly data to predict the energy use for the whole year. The cooling energy use of the Engineering Center building was chosen for this analysis. The "best" two-week models were considered for two cases of HVAC systems; dual duct CAV and dual duct VAV systems. Miami TMY weather file was used in the simulation. In each case, five different options of accounting for the occupancy variable (regressor) are used; basically fractions between 0 and 1, listed by order of simplicity:

Option 1: "True" occupancy, based on a walk through survey of the building,
Option 2: Surrogate occupancy derived from lighting and equipment load profiles with Eq.(4),
Option 3: Surrogate occupancy simply derived from the lighting and equipment loads by dividing all values by the absolute maximum value of the lighting and equipment consumption,
Option 4: Surrogate occupancy which has a value of 1 during weekdays business hours, 0 outside; and 0.33 during weekends for the same business hours, and 0 outside, and
Option 5: Surrogate occupancy which has a value of 1 for weekdays and 0 for weekends.

Table 1 shows the long-term prediction results (whole year), obtained by considering the five occupancy variable options described above in the best two-week (SMLP) modeling. The best two-week period for Miami, is April 10-23.

Table 1 The long-term prediction results (whole-year) of the SMLP model of the Engineering Center cooling energy use, Miami, FL, with different occupancy variable options.

	CAV		VAV	
Option	CV(%)	MBE(%)	CV(%)	MBE(%)
1	5.65	-0.36	12.74	1.75
2	5.68	0.43	13.51	4.01
3	9.37	7.39	27.63	24.06
4	7.76	1.22	21.60	6.30
5	11.76	7.54	33.04	24.49

Option 2 (the *linear transformation* surrogate variable) shows results comparable to using an extensive walk-through survey (option 1) of the building to obtain the occupancy schedules, in both CAV and VAV cases. Thus, there appears to be no need to conduct such occupancy surveys, and the occupancy variable (OCCUP) when using an SMLP approach can be simply derived from the lighting and equipment schedules (Eq. 4).

Options 3, 4, and 5 show deterioration in the prediction results. It is worth noting that option 4 provides better results than option 3; basically because in option 3 the maximum value encountered in the lighting and equipment loads naturally comes from a *weekdays* daytype and then used for normalizing all daytypes (weekdays, weekends, vacations, semester breaks). Obviously, if a maximum value of lighting and equipment load is found for each daytype and then used for normalizing, the corresponding data would lead to much improved results. Option 5, which is a simple flag variable (a 0-1 indicator); 1 for weekdays, 0 otherwise, is shown to be very simplistic and the poorest among all options evaluated.

Conclusion and discussion

Most simple linear regression (SLR) models assume the energy use as a function of outdoor temperature only, and can be used effectively at a monthly or a daily time scale, thus do not require the use of a separate variable for occupancy. However, when an inverse model is used at an hourly time scale, including separate variables for the driving factors becomes more effective, and thus the multiple linear regression (MLR) models become better candidates. Abushakra (2001) showed the advantage of including four driving variables in the hourly modeling of the energy use: (1) outdoor temperature, (2) outdoor specific humidity potential, (3) lighting and receptacles, and (4) occupancy. This paper showed that the occupancy variable can be derived from the lighting and receptacles load profiles that are becoming more and more available (Abushakra et al. 2000), and be used accurately in the inverse building energy models.

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