Quantifying Occupant Energy Behavior Using Pattern Analysis Techniques

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Occupant energy behavior is widely agreed upon to have a major influence over the amount of energy used in buildings. Few attempts have been made to quantify this energy behavior, even though vast amounts of end-use data containing useful information lay fallow. This paper describes analysis techniques developed to extract behavioral information from collected residential end-use data. Analysis of the averages, standard deviations and frequency distributions of hourly data can yield important behavioral information. Pattern analysis can be used to group similar daily energy patterns together for a particular end-use or set of end-uses. Resulting pattern groups can then be examined statistically using multinomial logit modeling to find their likelihood of occurrence for a given set of daily conditions.

These techniques were tested successfully using end-use data for families living in four heavily instrumented residences. Energy behaviors were analyzed for individual families during each heating season of the study. These behaviors (indoor temperature, ventilation load, water heating, large appliance energy, and miscellaneous outlet energy) capture how occupants directly control the residence. The pattern analysis and multinomial logit model were able to match the occupant behavior correctly 40 to 70% of the time. The steadier behaviors of indoor temperature and ventilation were matched most successfully. Simple changes to capture more detail during pattern analysis can increase accuracy for the more variable behavioral patterns. The methods developed here show promise for extracting meaningful and useful information about occupant energy behavior from the stores of existing end-use data.

INTRODUCTION

Background

Occupant behavior is widely agreed to have a large influence over the amount of energy used in residences. But human behavior is often felt to be too random for serious quantitative study. This work examines residential occupant energy behavior using statistical techniques and shows that behavior is not as unpredictable as it is assumed to be.

Many studies of behavior on residential energy use have been done. One of the most prominent is the study of a group of townhouses in Twin Rivers, New Jersey, performed by researchers at Princeton University (Socolow, 1978). The main objective of this study was to observe occupant energy consumption and conservation behavior. One analysis of the collected data compared the energy use of ‘‘movers’’ and ‘‘stayers’’ during two winters. The occupants of the ‘‘stayers’’ townhouses remained the same for both winters, while the ‘‘movers’’ group had new occupants during the second winter. The researchers found the standard deviation of the ‘‘stayers’’ natural gas consumption to be twice as high as that of the ‘‘movers’’ (Sonderegger, 1977/78), indicating that most of the variation in energy use was due to occupant behavioral differences. Natural gas use between seemingly identical townhouses (three-bedroom, interior units with double pane windows) during the same winter varied by at least a factor of two.

Similar studies of residential air conditioning use were done in Davis and Lodi, California. In the Davis study, summer electricity use of houses varied by a ratio of more than 2.3 to 1 (Cramer et al., 1984). Modeling the Davis buildings using the DOE-2 building energy model showed that self-reported behavioral variables, such as thermostat setting and appliance scheduling, explained 50% of the variation in energy use between houses. In the Lodi study, summer electricity use varied from house to house by a factor of four (Cramer et al., 1985). Inclusion of ‘‘social’’ factors such as education level, income, number of household members, and knowledge about energy and the environment were found to improve the prediction capability of statistical regressions for electricity use from a reliability of 51% to 58%.

Another study of residential energy use was part of the End-Use Load and Consumer Assessment Program (ELCAP) commissioned by the Bonneville Power Administration to study the energy use for space heat, water heaters and energy intensive appliances in the Pacific Northwest (Miller et al., 1990, 1991; Pearson, Miller and Stokes, 1988). Even when the houses studied are separated into groups according to climate zone and type of construction, energy use varies by more than 3 to 1 in these groups. A bit of pattern analysis was performed on the ELCAP data. Thermostat settings from the ELCAP houses were inferred from indoor temperature measurements and studied to find the two most common patterns of thermostat control (Connor and Lucas, 1990):

(1) constant temperature setting throughout the day (40% of the time),

(2) nighttime thermostat setback and morning setup (20% of the time).

The monitoring projects referenced above underscore the dominant effect of behavior on energy use. Variations in energy use between similar residences are typically a ratio of 3 to 1 and these variations are attributed to the occupant's energy choices and behaviors. Clearly, a better understanding of these behaviors will lead to better predictions of energy use.

Many researchers believe the effect of behavioral variations will average out when studying buildings in aggregate. This was not seen to be the case in the Davis, California study of summer electricity use (Vine et al., 1982). Aggregated results from DOE-2 energy models of each house were still off from the actual energy use by 18%. This suggests that accurate energy use predictions even for aggregated building groups cannot be made without knowing more about the residents of these groups. Accurate predictions can only be made by understanding ''average'' occupant behavior, and this ''average'' behavior may be different for different groups of people.

Day-typing or day-type segmentation is a statistical classification method often used to classify energy end-use behavior (Meagher, 1985). In this method a choice is made to group common days together, typically using at least the 2 groups of weekdays and weekends. More groupings can be made to separate out individual weekdays, Saturdays and Sunday and holidays. Day-typing assumes that end-use behavior is dependent on the day of the week, which may or may not be true of any given data set. In contrast, the classification method developed in the study groups daily behaviors together based on the similarities of their load shapes. These similarities are found from statistical analysis of actual daily load shapes. After the grouping is done multinomial logit analysis is used to see if the groups correlate with day of the week and other time and weather variables.

Scope

Four statistical methods have been tested and found useful in this study of energy behavior:

(1) daily time-series averages and standard deviations,

(2) frequency distributions,

(3) assignment of days to pattern groups,

(4) multinomial logit analysis to examine pattern group choice.

These methods were tested using data from four heavily instrumented, occupied houses studied in a University of Washington project (Ferris, 1988). These houses were originally built to compare a proposed building energy standard with the then-current 1980 building codes for the state of Washington. Two of the houses were built to the 1980 codes, the other two to the proposed Model Conservation Standards (MCS) (Byers, 1991), otherwise they are identical in layout and construction. These test houses are heated with electrical baseboard heaters, and have a separate forced air ventilation system and kitchen and bathroom fans. Each house contained an electrically powered water heater, range, refrigerator, dishwasher, garbage disposal, clothes washer and clothes dryer. Power measurements were made every 4 seconds and averaged over each 15 minute period of the day.

The houses were occupied by graduate students and their families. Each family consisted of a husband, wife and two or more children. Twelve different families lived in these houses during the period from 1987 to 1994, four families for three consecutive years and two families for two years. Occupants paid their own utility bills, although they did receive a break in rent for participating in this study. Although the families are demographically similar, they were found to have varying energy behaviors.

The houses were studied during each heating season, assumed to last from October through April, from 1988 to 1994. Data for five different energy behaviors were collected from the houses:

(1) indoor temperature preferences,

(2) ventilation energy load,

(3) water heater energy use,

(4) kitchen & laundry energy use,

(5) miscellaneous energy use.

These five behaviors are under direct control of the occupants, as opposed to space heating energy use which is indirectly controlled by the thermostat setting and heat produced by other appliances in the house.

Indoor temperature preferences are used to estimate thermostat setting behavior of the occupants, accounting for artificial highs due to overheating, and are divined from study of simultaneous values of indoor temperature and space heat energy use (Gartland, 1995). Ventilation loads are calculated from heating load imposed on the house in order to bring the ventilation air up to the indoor temperature. Kitchen and laundry energy use includes all energy used by the house's major appliances except the water heater. Miscellaneous energy use includes the energy used by all built-in light fixtures and electrical outlets throughout the house.

These five behaviors were studied for each family separately during each heating season of their occupancy. Measured data was checked and processed to yield 96 quarter-hour values for a complete day for each of the five behaviors. These days of behavioral values were manipulated statistically to find each families' patterns of behavior.

METHODOLOGY

Averages and Standard Deviations

A simple and effective way to study behavioral data is to look at time-series averages and standard deviations. In this study, the average of the daily behavioral values are taken at each time step during the day to get an average value of the behavior versus time of day,

$$average_{time\ t} = \sum_{n=1}^{number\ of\ days} behavior\ value_{time\ t} \Big/ number\ of\ days. \qquad (1)$$

The standard deviation is found similarly for each time step,

$$sd_{time\ t} = \sqrt{\sum_{n=1}^{number\ of\ days} (behavior\ value_{time\ t} - average\ value_{time\ t})^2 \Big/ number\ of\ days.} \qquad (2)$$

The average and standard deviation of behaviors can be plotted versus time of day to show daily variation with time.

Frequency Distribution

It is often useful to know more than just the average and the standard deviation of a particular behavior over a daily period. The frequency distribution is a way of showing how often a particular value of a behavior occurs over the season or time period of interest. The frequency distribution is found by breaking up the possible values of behavior into equally sized bins, and then counting the number of actual behavioral values falling into each of those bins. The number of occurrences can be normalized by dividing by the total number of values. The frequency distribution can be visualized by plotting behavioral values on the x axis, and the number or percent of total occurrences on the y axis.

The frequency distribution can be compared to a normal distribution for the behavioral data. The normal distribution is found using the average, μ, and standard deviation, σ, of the data in question in the following equation for probability density,

$$f(x) = \exp[((x - \mu)/\sigma)^2/2]/2\pi. \qquad (3)$$

An example of a frequency distribution for the temperature preference behavior is shown in Figure 1. The distribution was found separately for different time periods during the day—midnight to 6am, 6am to 9am, 9am to noon, et cetera. The normal distribution is shown in the plots as a dark solid line.

Figure 1. *Frequency distribution curve for the temperature preference behavior of house 3 in the 1987–88 heating season.*

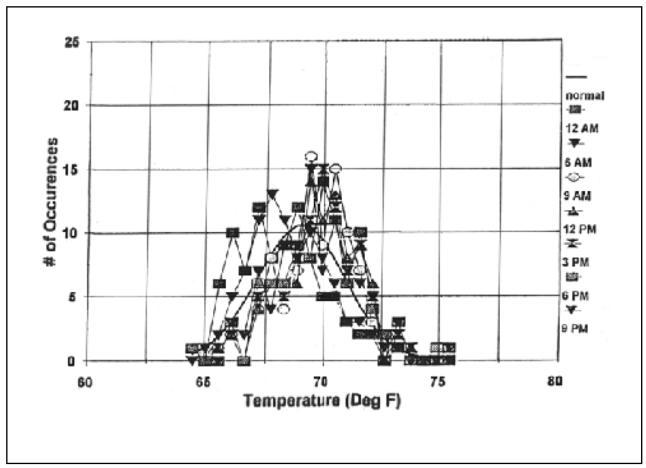


Figure 2. *Example of the pattern code assignment for Julian day 342 in house 3 during the 1987–88 heating season.*

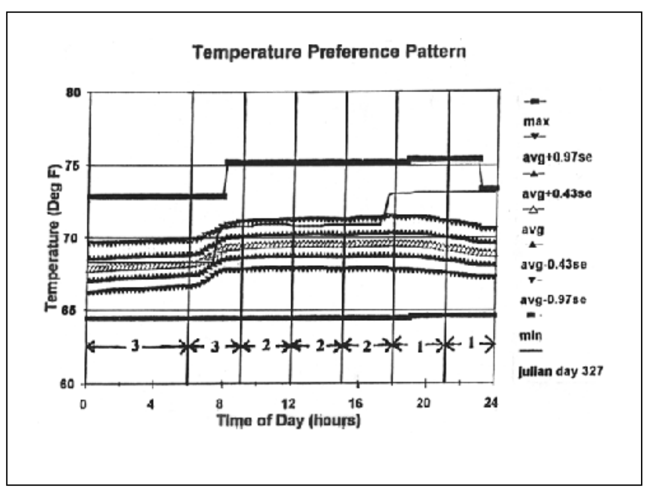
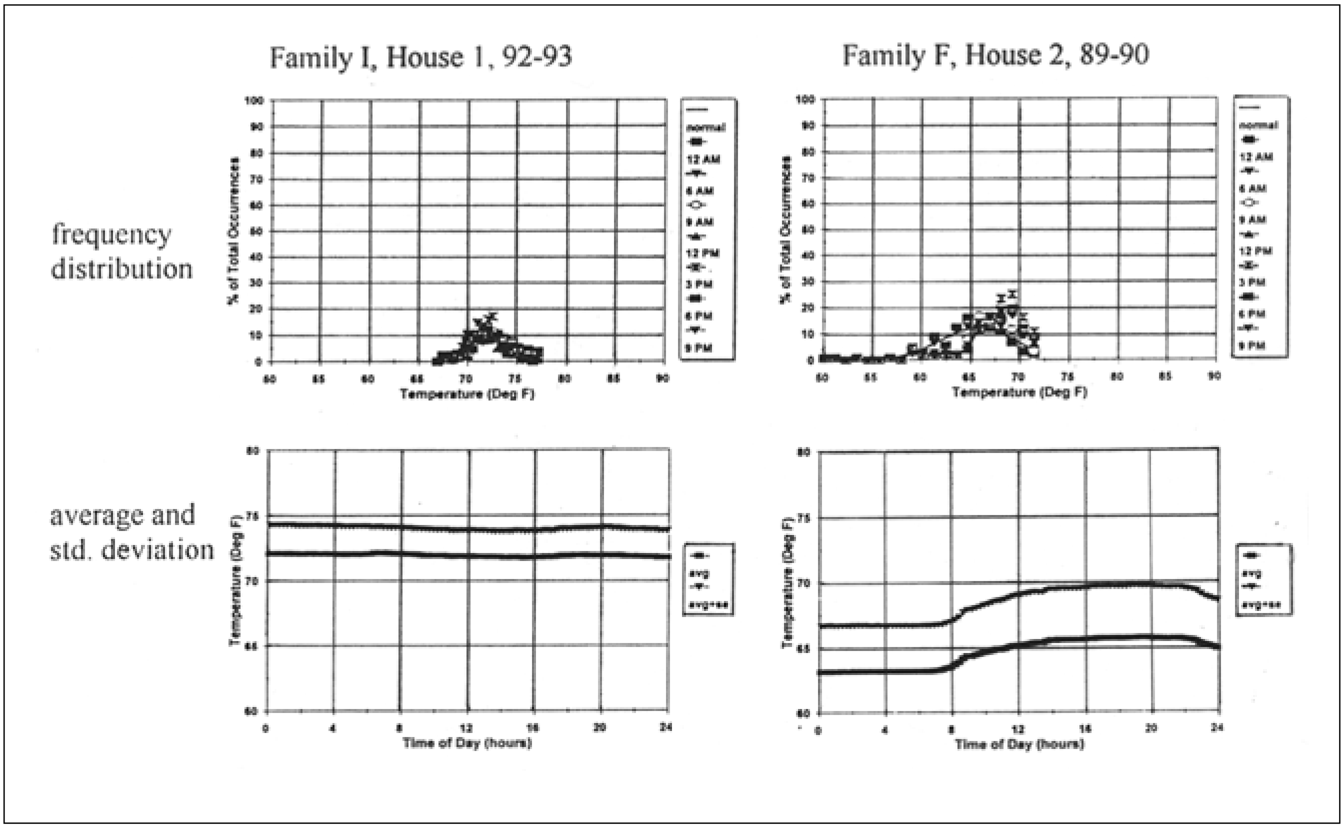


Figure 3. *Frequency distribution curve and average and standard deviation plots for the temperature preference behavior. Constant values are illustrated by Family I's plots, while setup/setback behavior is seen for Family F.*



Pattern Group Assignment

Instead of grouping energy behaviors together based on the day of the week, as in day-typing algorithms, a new algorithm was developed to group together days with common behavioral load shapes or patterns (Gartland, 1995). This algorithm first assigns each day a pattern code and then iteratively groups days with similar codes together.

Pattern codes are assigned in reference to the frequency distribution. For illustration purposes, assume the normal distribution shown in Figure 1 represents the actual data. This distribution is broken into six sections of equal area. The dividing lines between each sixth for a normal distribution are found mathematically to lie at

maximum value,
average + 0.97*standard deviation,
average + 0.43*standard deviation,
average,
average − 0.43*standard deviation,
average − 0.97*standard deviation,
minimum.

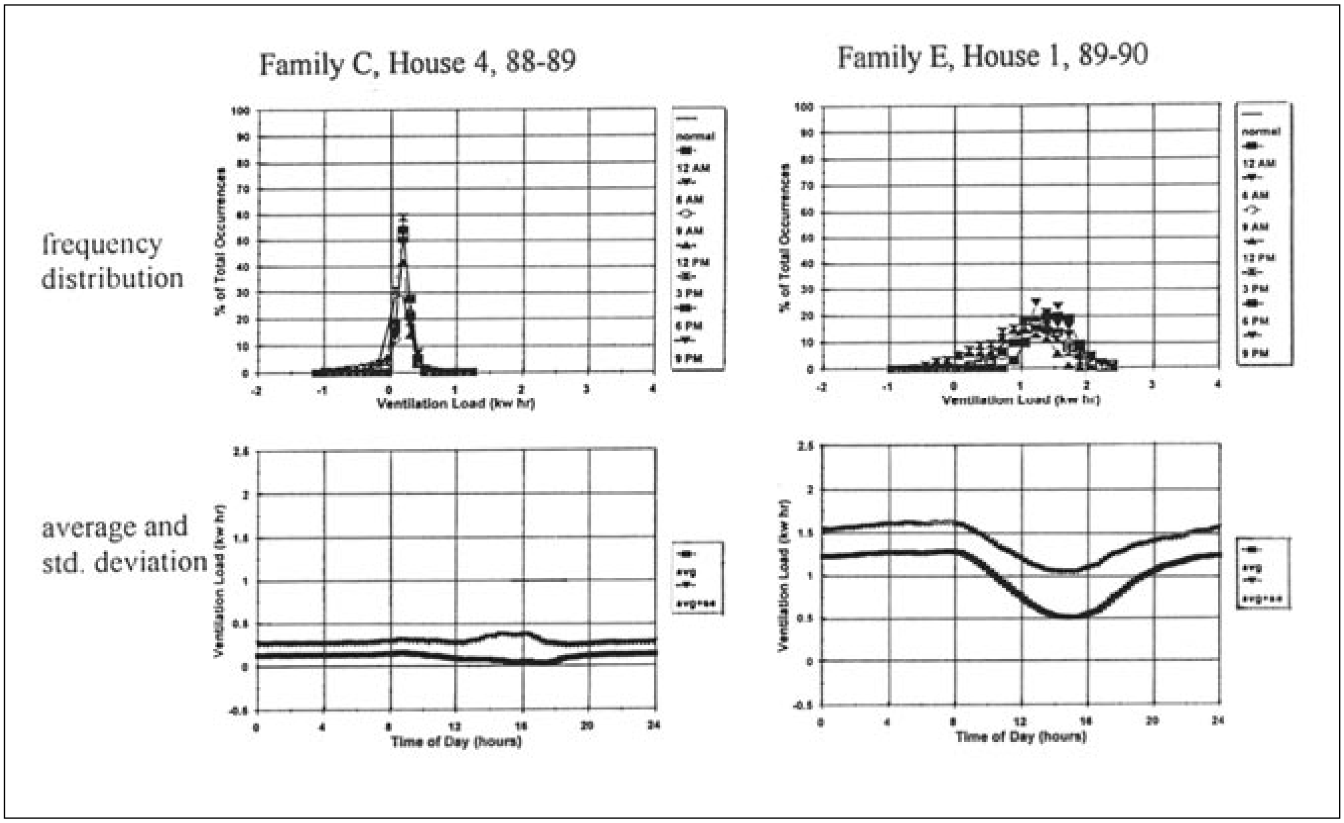
These values are plotted versus time of day in Figure 2, along with an actual day of data from the period of interest, Julian day 327. The day is broken into 7 time periods. To assign the pattern code for day 327, the actual day's data is compared to the sixth values to see where it falls in each time period. Numbering the code values from 1 to represent the highest sixth to 6 for the lowest sixth, Julian day 327 takes the pattern code of 3-3-2-2-2-1-1. Pattern codes for each behavior are assigned to each day of collected data.

Note that there is flexibility in the level of detail available to the pattern code. Different numbers of sections, and different numbers and designations of time periods can be chosen depending on the data and the level of accuracy needed.

Once the pattern codes are assigned to each day, the days are iteratively assigned to groups. In the first iteration, days with the same pattern code are grouped together. In the second and proceeding iteration, groups with similar pattern codes and the lowest combination errors are combined. The combination error is defined mathematically as,

$$\Delta_{error} = [\sigma_{group1\&2}(n_{group1} + n_{group2}) - \sigma_{group1}n_{group1} - \sigma_{group2}n_{group2}], \quad (4)$$

Figure 4. *Frequency distribution curve and average and standard deviation plots for the ventilation load behavior. Family C uses little ventilation, while Family E used forced ventilation through the house's ducting system.*



where the value of σ is the average of the standard deviation of all group members at each time step, which for the case of 96 quarter-hour time steps for each day is,

$$\sigma_{group} = (\sigma_{time\ step\ 1} + \cdots + \sigma_{time\ step\ 96})/96. \tag{5}$$

Pattern groups are combined until there are no more groups with sufficiently similar pattern group codes. The test of sufficient similarity for this study was deemed to be when pattern codes were off from each other by no more than the number of digits in the code, for example,

$$\begin{array}{rcccccccc} & & 3 & 3 & 4 & 4 & 4 & 4 & 3 \\ & - & \underline{3} & \underline{4} & \underline{4} & \underline{4} & \underline{4} & \underline{4} & \underline{4} \\ \text{abs}\,\Delta & = & 0 + & 1 + & 0 + & 0 + & 0 + & 0 + & 1 = 2. \end{array}$$

Since 2 is less than 7, the number of digits in the pattern code, these two groups are deemed sufficiently similar to be combined.

Multinomial Logit Analysis

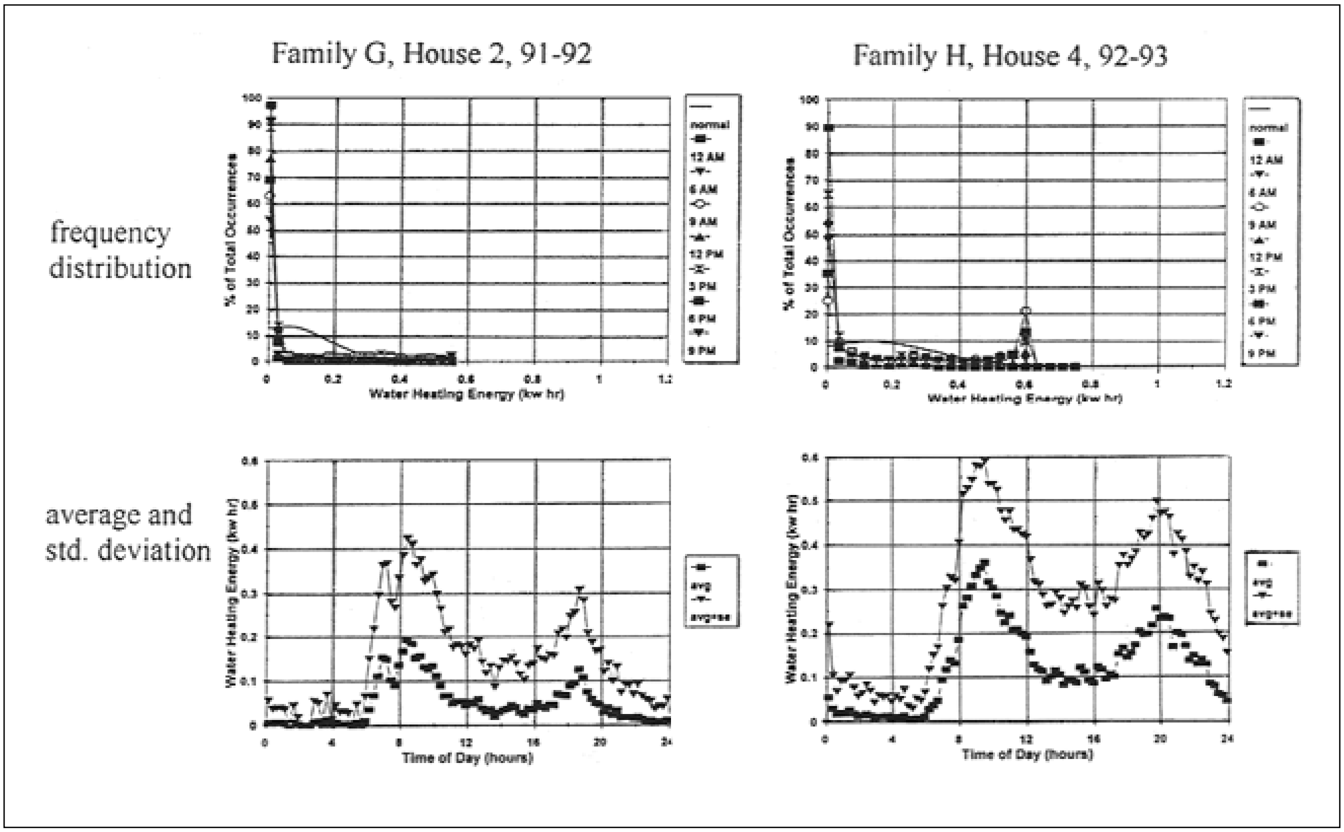
In order to predict household energy use accurately with behavioral pattern groups, some method must be found to predict which behavioral patterns will be used on any particular day. The simplest assumption is that each pattern group occurs randomly with a distribution equal to its number of occurrences -a weighted random sampling distribution. A better approach is to find out what variables influence the choice of particular behavioral patterns. This is done using multinomial logit analysis, a statistical choice modeling technique (Kennedy, 1985).

The multinomial logit model finds utility functions for each of the different pattern choices available for any energy behavior. Probabilities of the patterns' occurrence can be found from the utility functions:

$$\begin{aligned} U_1 &= B_{10} + \beta_{11}(\text{var}_1) + B_{12}(\text{var2}) + \ldots, \\ U_2 &= B_{20} + B_{21}(\text{var}_1) + B_{22}(\text{var2}) + \ldots, \\ &\;\;. \\ &\;\;. \\ U_n &= B_{n0} + B_{n1}(\text{var}_1) + B_{n2}(\text{var 2}) + \ldots, \end{aligned} \tag{6}$$

and,

Figure 5. *Frequency distribution curve and average and standard deviation plots for the water heating behavior. Family G uses a low amount of water heating energy, while Family H is a high energy user.*



$$P_1 = \frac{e^{U_1}}{\sum\limits_{k=1,n} e^{U_k}},\ P_2 = \frac{e^{U_2}}{\sum\limits_{k=1,n} e^{U_k}},\ldots\ P_n = \frac{e^{U_n}}{\sum\limits_{k=1,n} e^{U_k}}, \qquad (7)$$

where the U's are the utility functions, dependent on variables var1, var2, etc., with regression coefficients B_{10}, B_{11}, etc., and with probabilities of occurrence P_1, P_2, etc.

The difficulty in multinomial logit modeling, as in all statistical modeling, is choosing the right independent variables. In order for the logit model to be a useful prediction tool, the variables chosen need to be easily known or assumed for prediction purposes. The variables chosen for this study are listed in Table 1.

RESULTS

Average & Standard Deviations and Frequency Distributions

Energy behaviors were studied for each of the 4 houses during each heating season, for a total of (5 behaviors) $\times$ (4 houses) $\times$ (5 heating seasons) $=$ 100 separate cases studied. Figures 3 through 8 show the most typical of the average & standard deviation and frequency distribution plots for the five behaviors studied. Note that behavior varied substantially between households, even though the families were demographically similar.

Plots of temperature preference behavior showed two behaviors, one where the family kept temperatures relatively constant, and the other where setup and setback of temperatures is occurred (Figure 3). The average & standard deviation plots show at what time of day setups and setbacks typically occur. The frequency distribution curve for the setup/setback family does not follow the normal curve, being more heavily weighted at higher setup values, and carrying a ''tail'' of lower setback values.

Ventilation load behavior plots show whether or not households use the forced ventilation system provided in the houses (Figure 4). Some families have turned the system off, only turning on bathroom or kitchen fans sporadically. Other families keep the system running fairly continuously. Ventilation load is dependent on the outdoor air temperature, so dips in the ventilation load are seen in the afternoons when is it typically warmer outside.

Figure 6. Frequency distribution curve and average and standard deviation plots for the kitchen and appliance energy use behavior. Family C's kitchen energy use peaks in the morning, while Family J's energy use peaks in the evening.

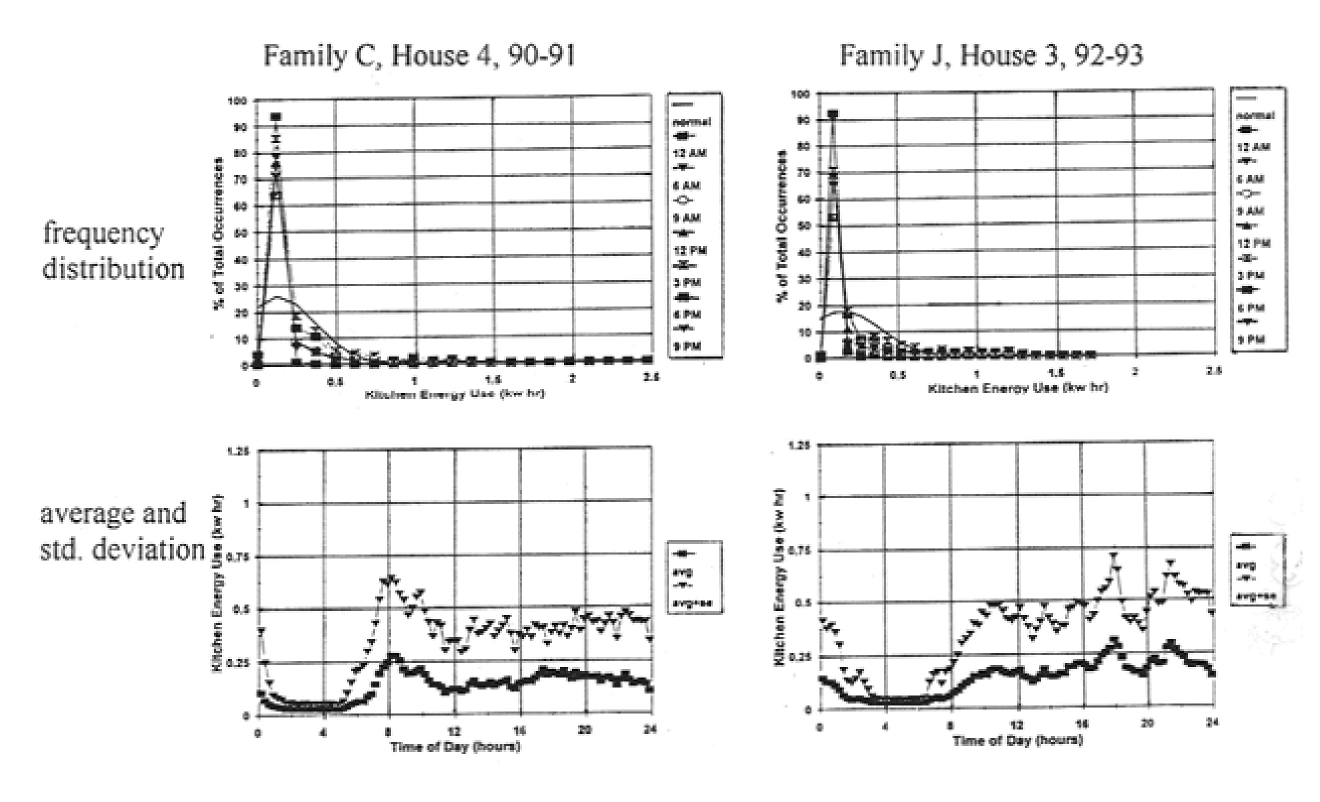


Table 1. *Percentage of Times Variables Were Found to be Significant in the Multinomial Logit Models, for Each Behavioral Pattern Type*

Variable	Temperature Preference	Ventilation Load	Water Heating	Kitchen & Appliances	Lights & Outlets	Total
Outdoor temperature	60	56	35	46	52	50
Wind speed	50	63	45	36	57	50
Horizontal insolation	65	44	50	36	33	46
Day of season	60	50	20	59	57	50
Day of week	32	26	13	9	11	18
Weekend day	35	2931	25	5	19	22
Month of year	5	1729	13	6	2	10
Holiday, break, finals	8	17	5	2	11	8

Plots of water heating energy show how much energy is typically used and at what time of day (Figure 5). The average and standard deviation plot differentiate clearly the high and low hot water use families. The frequency distribution curves for water heating are somewhat less indicative of high or low use behavior, mainly because the water heater is an on-off appliance. Both high and low use families have a spike in the frequency distribution curve at zero energy

Table 2. *Multinomial Logit Modeling Results, Averaged from Three Models of Each Behavioral Type*

Variable	Temperature Preference	Ventilation Load	Water Heating	Kitchen & Appliances	Lights & Outlets	Overall Average
Number of observations	138	124	111	96	127	119.2
Number of patterns	8	7	12	11	10	9.6
Number of variables	43	39	33	29	32	35
Confidence level	85	99	99	99	88	94
% Correctly predicted	43.0	61.4	46.8	46.9	51.4	49.9
% Random weighted	15.5	18.3	21.5	18.7	17.8	18.4
Improvement ratio	2.8	3.4	2.2	2.5	2.9	2.7

use. For the high use family a second spike is seen at 0.6 kWh, the maximum capacity of the water heater. The low use family does not use enough hot water at any one time to bring their water heater to peak capacity for a complete 15 minute time period.

Kitchen and appliance energy use is illustrated best by the average & standard deviation plots, which are able to show temporal peaks in energy use (Figure 6). The frequency distributions are not very useful for studying behavior, as refrigerator cycling dominates the bulk of the occurrences.

Figure 7 shows the average & standard deviation plots of lights & outlets energy use for 2 houses over five heating seasons, and Figure 8 shows the frequency distributions. Note that families C and G were each resident for three seasons, and family H for two seasons. These plots show very distinctive and consistent patterns for each family from season to season.

Pattern Group Analysis

Figure 9 shows an example of pattern groups resulting from the pattern classification algorithm. The reason for performing pattern analysis, is contained in the statistics listed in Figure 9. The standard error that results by representing behavior with multiple patterns is much smaller than the standard error for one average pattern. Figure 10 plots a normalized standard error reduction versus the normalized number of pattern groups. Each of the five behavioral pattern types is represented by a different symbol. The standard errors are reduced to between 20 and 90% of the single pattern group value. The temperature preference and ventilation load patterns show the largest reductions in standard error, on average reduced to 33% of the single pattern value. The water heating, kitchen & appliances and lights & outlets behaviors have smaller reductions in standard error.

Multinomial Logit Analysis

Three multinomial logit models were developed for each of the five behaviors. Each model looked at one energy behavior of one household during a single heating season. The models are developed to predict which behavioral pattern type is likely to occur on a given day. Behavioral pattern types for all days in the heating season were regressed against the variables listed in Table 1. The households modeled were chosen to cover the spectrum of observed behaviors seen in the average & standard deviation and frequency distribution plots. Results from the three models are averaged together for each of the five behaviors and presented in Table 2. The information given in this table is:

- # observations—number of days of data collected in each season,
- # patterns—the number of patterns found by the pattern classification algorithm,
- # variables—the number of significant variables in the final model,
- confidence level—reflects the significance of all variables in the final model
- % correctly predicted—the percent of daily pattern choices that are estimated to be correctly predicted by the logit model,
- % random weighted—the percent of daily pattern choices that would be correctly predicted by a random guesses weighted by the percentage of occurrence of each pattern,
- improvement ratio—the ratio of the correctly predicted and the randomly weighted percentages, showing

Figure 7. *Average and standard deviation plots for the lights and outlets behavioral pattern for the heating seasons from 1988–89 through 1992–93. Family behavior is strikingly consistent from season to season, and distinct for different families.*

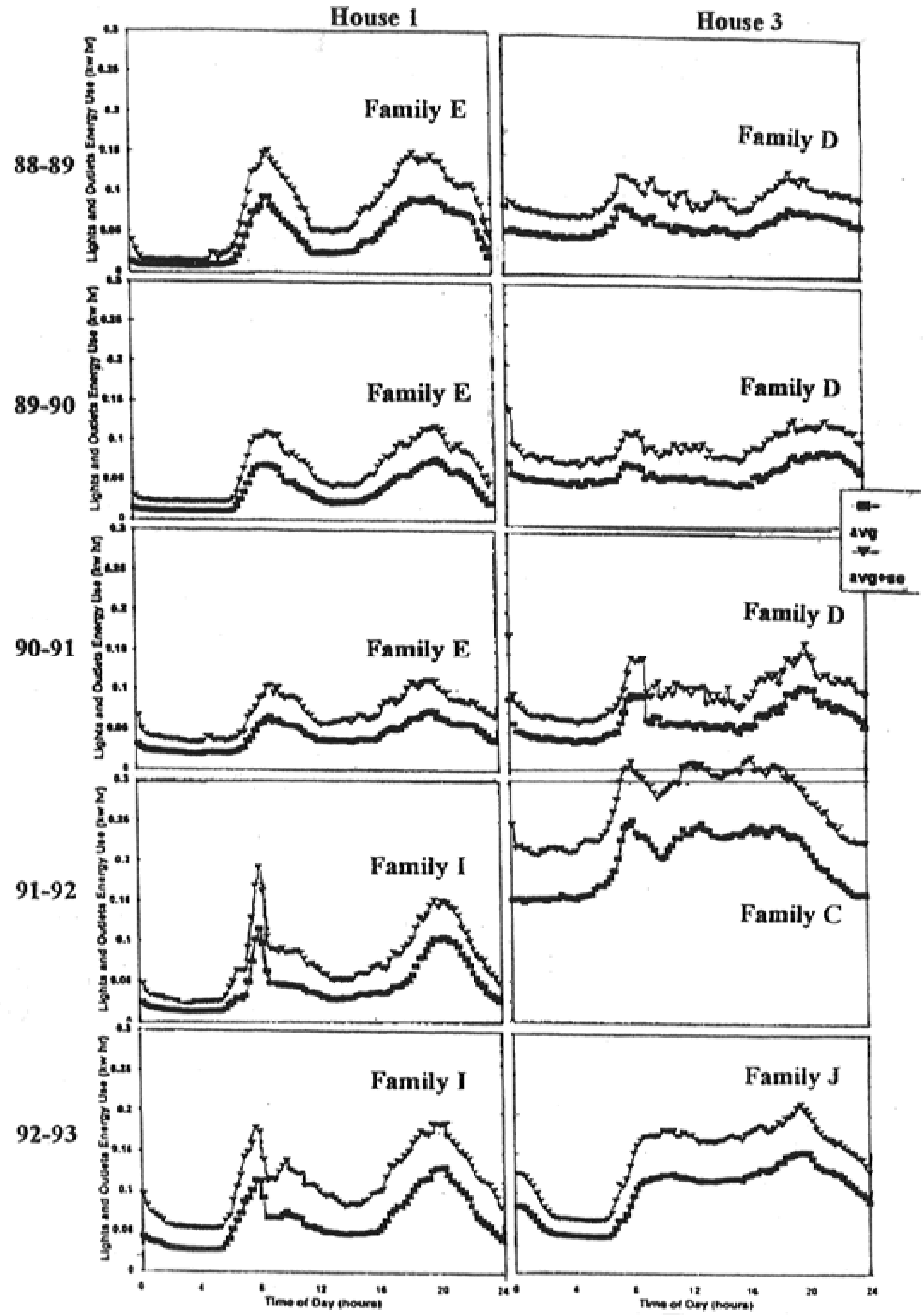


Figure 8. *Frequency distribution curves for the lights and outlets behavioral pattern for the heating seasons from 1988–89 through 1992–93. Family behavior is strikingly consistent from season to season, and distinct for different families.*

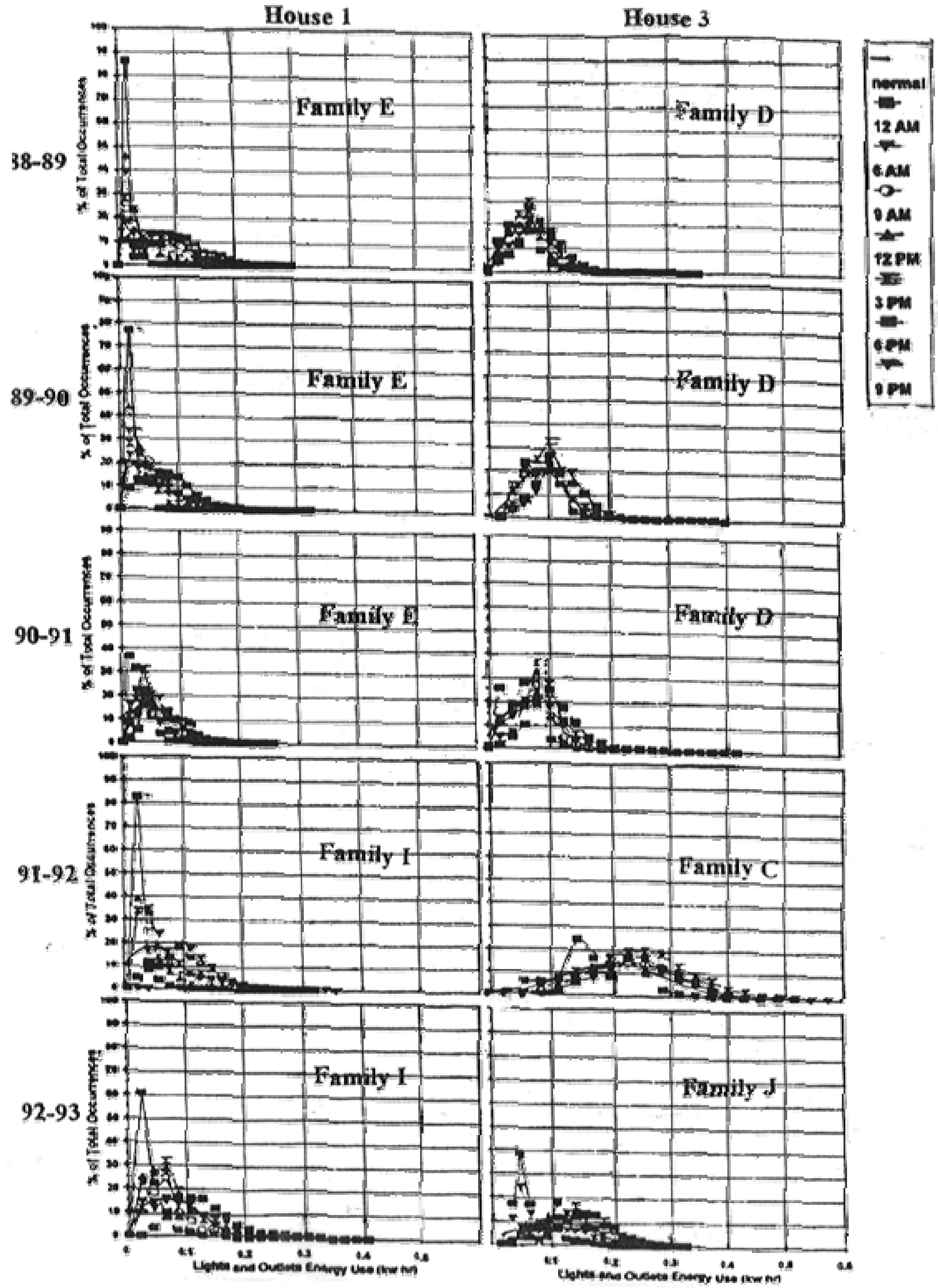
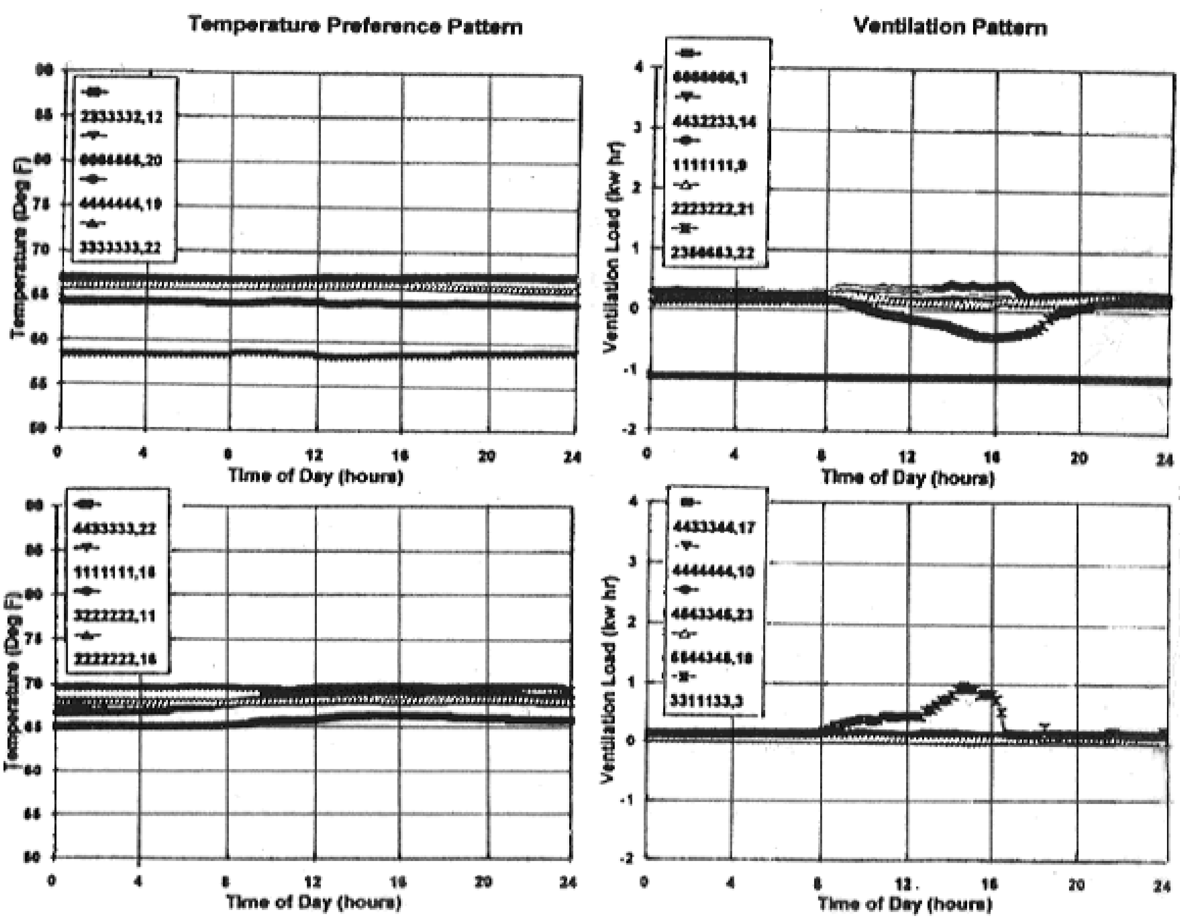


Figure 9. *Resulting pattern groups for Family C, house 4, 1988–89 heating season. Temperature preference and ventilation behavioral patterns are shown, and statistics on standard errors are included.*

House 4, 88-89 Season   138 days   **Family C**

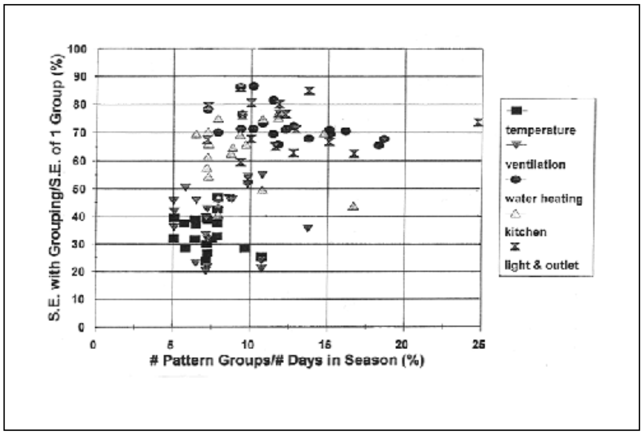
pattern	# patterns	std. error	std. error of 1 pattern
temperature	8	1.019	3.594
ventilation	10	0.054	0.169
water heating	14	0.097	0.136
kitchen	12	0.114	0.182
lights & outlets	13	0.054	0.071



how much the logit model is able to improve on a random weighted guess.

The logit models contain many variables because each model is actually a series of equations, one equation for each pattern group. The level of confidence in the models was quite high, indicating that for all these models the variables chosen are producing valid results. The improvement ratios for all behavioral types are 2.2 or higher. This means that the prediction capability of the multinomial logit models is at least twice as good as random guessing. On average, the behavioral patterns used on a given day are predictable half of

Figure 10. Standard error reduction due to pattern grouping, shown separately for the five behaviors studied. Pattern grouping is shown to be more effective for temperature preference and ventilation load behaviors.



the time. These results are very promising when considering the generic attributes of the variables used in the models.

Not all the variables chosen were significant in all the models. Table 1 shows the percentage of times when each variable was significant in the choice of an energy behavior. Overall, the various weather variables were most often important indicators of pattern choice—significant about half the time. Interestingly, the day of the week/weekend indicators are only significant on average about 20% of time. This calls into question the practice of day-type segmentation. It may not be realistic for behavior to be similar on certain days of the week. Pattern classification and multinomial logit analysis of pattern choices has the potential to group and predict energy behavior more accurately than the traditional day-typing schemes.

CONCLUSIONS

This four houses and twelve families analyzed in this work represent a relatively small data set, but variations in energy behaviors were identified and characterized with the statistical methods used in this study. The average & standard deviation plots uncovered behavioral variations between families over a typical day. Frequency distribution curves were useful for visualizing behaviors which can vary in small increments over a large range, although they may not always be helpful when looking at a single end-use with on-off behavior (like a water heater), or for a combination of end-uses dominated by an on-off appliance (like a refrigerator).

The pattern classification algorithm was shown to work and to reduce standard error. The temperature preference and ventilation load patterns have the most potential for error reduction, with reductions from 20 to 50%. The other three patterns showed less promise, with reductions between 50 and 90%, although the classification method can be enhanced by changing the number of time steps or energy value ranges to capture more of this variation.

The methods developed may be more accurate than day-type segmentation schemes currently being used. The patterns studied in this work were found to depend on day of the week on average about 20% of the time. Grouping behaviors together based on their load shape similarities eliminates the necessity of assuming behaviors are similar on certain days of the week.

Perhaps the most significant finding of this work is how predictable the patterns turned out to be. Even with the fairly generic set of weather values, days of the week, etc. used as variables, the multinomial logit models are able to choose the correct behavioral pattern used by each household half the time. This is much higher than the ~20% of the time estimated for weighted random guesses. This is even more impressive when it is realized that the behavioral variations being detected and predicted are relatively small, since this analysis was limited to one family at a time.

The strategies used here to analyze one family at a time could also be used to classify the combined behaviors of many families. Averages or frequency distribution curves for individual families or sets of families could be used in place of the daily data used in this study. Logit modeling could then link family statistics (size, ages, income levels, education, etc.), weather variables and day of week variables to these new pattern groups.

These methods show great potential for producing a meaningful analysis of existing residential end-use data sets. Pattern analysis could give typical behavioral/use patterns for and end-use or set of end-uses, and logit analysis can help specify when each of the behaviors are most likely to occur. This information could be linked to building-scale or macro-scale energy prediction models for an improved modeling and forecasting tool.

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