Hourly Conditional Demand Analysis of Residential Electricity Use

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A conditional demand analysis was undertaken for a New York State utility to estimate typical hourly electricity use in fifteen residential end-uses for two day-types and four seasons. Most hourly conditional demand analyses that have been done to date have ignored the effect of weather on hourly load patterns. In contrast, this study developed hourly load estimates that are weather-sensitive. An innovative Bayesian approach was employed in which previously estimated monthly unit electric consumption estimates and older metered household load observations were used to specify priors to be incorporated into a generalized least squares estimation process. For all but one end-use, the Bayesian priors were weighted equally with the actual load data. The effect of the priors on the final estimated coefficients depended on the strength of the correlation between the actual observations on total household electricity use and the explanatory variables, such as square footage and the stock of household appliances. This Bayesian approach made it possible to estimate reasonable hourly load shapes even in cases where multiple end-uses had very high saturations. The resulting estimates were developed into load shape representations that can be used to forecast future electric hourly load. The results can also be used in demand side management analyses to estimate unique end-use load shapes for households with different physical and demographic characteristics.

Introduction

Estimates of hourly electricity use for residential and commercial space heating, cooling, and other end-uses are highly valued by electric utilities. End-use hourly load estimates can be used to develop forecasts of electricity demand that will reflect the effect of shifts in end-use saturation and intensity levels on hourly and peak load generation requirements. End-use hourly load equations that relate hourly load use to household physical and demographic characteristics can also be valuable in selecting customers for demand-side management programs. End-use hourly load shapes can also be useful in rate design analyses.

Utilities have a number of alternatives available for developing estimates of hourly electricity use in residential and commercial end-uses. Metering, which can provide good estimates of end-use hourly electric load, is costly. In addition, end-use metered estimates can be misleading if the metered circuits include more than one end-use. End-use metering projects are also usually conducted for small sample sizes that preclude their use for developing load estimates for different types of households, which are needed for developing and evaluating alternative DSM programs.

One low cost alternative to end-use metering for developing end-use hourly electric load estimates is conditional demand analysis. In this approach, a statistical model is used to disaggregate total household hourly electricity use into end-use hourly load, based on each household's stock of appliances and physical and demographic characteristics.

Much conditional demand analysis has been done since the original work of Parti and Parti (Parti and Parti 1980). Today, it is a fairly common practice to use conditional demand analysis to estimate *annual,* or *monthly,* unit electric consumption estimates for residential end-uses and electricity use intensities for commercial end-uses. Conditional demand analysis has also been used to estimate hourly load profiles for residential and commercial end-uses. However, previous hourly conditional demand analysis has often been limited by the difficulty of estimating load shapes for end-uses that are confounded. For example, if 100 percent of the households have refrigerators and 98 percent have clothes washers, it will be very difficult to identify the amount of variation in total household hourly load that is attributable to these two end-uses.

Because of the inherent difficulty in estimating hourly end-use coefficients, especially for end-uses that are confounded, a number of alternative approaches have been developed to improve the estimation process. Some have used the results of annual or monthly unit electric consumption conditional demand analysis to develop variables for an hourly model (McCollister 1987). This approach is helpful in estimating the appropriate average hourly level of end-use load, but cannot help in determining the hourly end-use load pattern. More commonly, engineering models have been used to develop Bayesian priors of hourly end-use electricity use, which are then incorporated into a generalized least squares estimation. (Schon and Rodgers 1990; Rohmund et al. 1992; Caves et al. 1987.) However, the common limitation of these engineering models has been their inability to represent the human behavioral aspects of electricity end-use consumption.

In our analysis, an innovative Bayesian approach was used to perform a conditional demand analysis of residential electricity use in the service territory of a New York state utility. In this analysis, the Bayesian priors of electricity use for each end-use were estimated using the results of a previous monthly conditional demand analysis and load shape representations developed from an earlier residential household metering project.

Most hourly conditional demand analyses that have been done to date have ignored the effect of weather on hourly load patterns. In contrast, this study developed hourly load estimates that are weather-sensitive.

The results of this estimation process demonstrate that this approach offers a low cost means of developing hourly electric end-use consumption estimates. Utilizing these Bayesian priors yields reasonable estimates of hourly load levels even for highly saturated end-uses, which is usually not possible with ordinary least squares estimation. The results provide estimates of end-use hourly load that when summed match well with total household load. Combining annual unit electric consumption estimates with metered end-use load data can yield better priors than priors based on engineering models because they incorporate the effects of human behavior on end-use electricity consumption.

EPRI's Hourly Electric Load Model (HELM) was used throughout this project. First, HELM filled in missing values in the raw total household metered data. HELM also estimated the load shape representations that were used in specifying the priors for this analysis. These load shape representations were developed from an earlier end-use metering study (Blaney 1992). HELM plots also helped to visually analyze the total household metered data to determine the appropriate break points for the weather response functions estimated in the pre-processing phase of the project. Lastly, the final estimated coefficients from the conditional demand analysis were translated into HELM load shape representation files for forecasting future end-use electricity load.

Data Development and Pre-Processing

Electricity Use and Household Characteristics Data

Hourly household electricity consumption data were developed from a New York state utility's load research metered data for the period September 1, 1992 through August 31, 1993. The corresponding electric end-use appliance stock and physical and demographic characteristic data for each household were determined based on the results of a household energy usage survey which was completed in 1992. There were 375 households included in the household energy survey. However, after eliminating households for which there were no load research data, or for which some of the data were missing or flawed, load and survey data for a total of 181 households were included in the conditional demand analysis.

Observations on household hourly load were pooled into four season (summer, winter, spring, and fall) and two day-type (weekday and weekend) categories. Working with eight season and day-type categories, a total of 192 regressions were run for this analysis (4 seasons * 2 day-types * 24 hours).

If the hourly load observations were used for each household directly, there would be approximately 10,680 observations (60 weekdays * 181 households) for each of the weekday hourly regressions and approximately 4,344 observations (24 weekend days * 181 households) for each of the weekend hourly regressions. In order to reduce the number of observations for each hourly regression, and thus reduce the computation time and computer resource requirements to manageable levels, a pre-processing step was undertaken in which a piecewise linear weather response function was estimated for each household in each hour, season, and day-type combination. The functional form of this weather response function was as follows:

$$L_{it} = A_i + B_i * T_t + C_i * (T_t - BP_t) * D_t + e_{it}$$

where:

L_{it} = Electricity consumption in household i in period t
T_t = Temperature in period t
BP_t = Break Point temperature in period t
D_t = 1 if T_t > than BP_t
0 otherwise
e_{it} = error term for household i in period t

Figure 1 presents a winter season weather response function as defined by Equation (1) for an illustrative household with electric space heating. The temperature in this example ranges from 0 to 85 degrees with an assumed break point temperature of 31 degrees.

For households with electric space heating, B in Equation (1) should be less than zero indicating that as the temperature rises from 0 to 31 degrees the total household electricity use should decline. As the temperature increases above the break point temperature, total household electricity use should continue to decline, but at a slower rate. Thus, coefficient C in Equation (1) should typically be greater than zero. But, the sum of B+ C should be less than zero. Finally, as the temperature continues to rise the weather response function will flatten out at some temperature as the electric space heater is turned off.

Weather response functions like Equation (1) were estimated for each household for each hour in each of the eight season and day-type combinations. These weather response functions were then used to create three total household electric use pseudo-observations per season and day-type combination for each household in the data base. For example, in winter months, the first pseudo-observation estimated with the weather response function corresponded to the total household electricity use at the average temperature in the cold segment. This point is identified as L1 in Figure 1. The second observation corresponded to the estimated total household electricity use at the average temperature in the mild segment, L2 in Figure 1. The third observation corresponded to the estimated total household electricity use at 60 degrees, L3 in Figure 1, the temperature at which electricity use for space heating was assumed to be zero.

Weather response functions with identical structures were estimated for the spring and autumn seasons. Because the electricity use data were obtained from households located in upstate New York, there was little or no cooling load observable in these spring and autumn seasons. Piecewise linear weather response functions with a similar structure were also estimated for the summer season. However, for the summer season, the estimated B coefficients, as well as the sum of the B and C coefficients, in Equation (1) were expected to be positive for household with air conditioning, reflecting the increase in cooling load as the temperature increased.

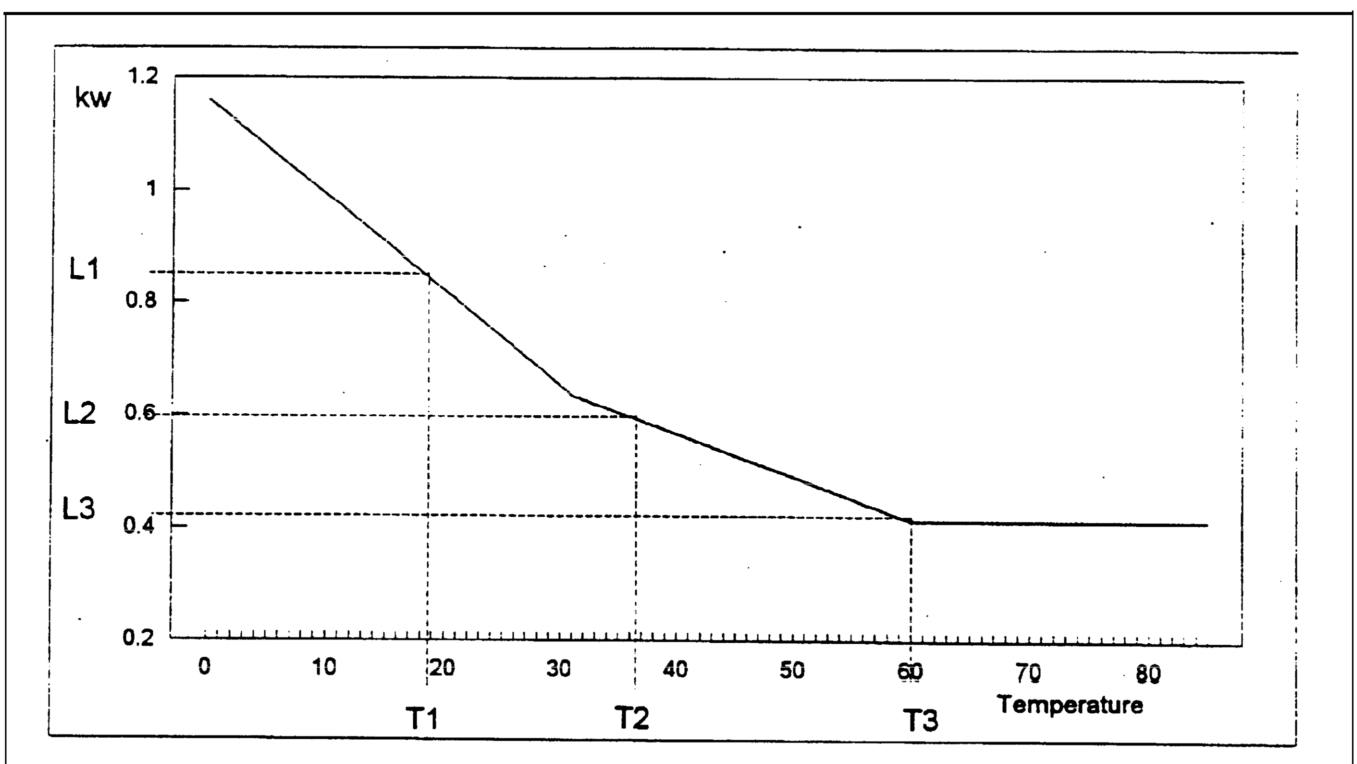

Figure 1. Illustrative Weather Response Function

Weather Data

The weather data used in this analysis were the actual hourly temperature for each household's region. For this purpose, the households in the data base were grouped into three weather regions: Albany; Syracuse; and Buffalo.

Estimation of Priors

The Bayesian priors on residential end-use electricity use developed for this analysis were derived from two components: estimates of total annual electricity use for each of the fifteen end-uses; and estimates of the distribution of end-use electricity consumption for each end-use across the 8,760 hours in the year.

The estimates of annual electricity use were obtained for each end-use from the results of a residential conditional demand analysis designed to estimate monthly unit electricity consumption estimates (Sebold, Mayer 1993). This conditional demand analysis was performed using load and survey data for each of the New York state utilities.

The coefficients from this New York state conditional demand analysis were used to estimate the annual electricity use for each of the households in the hourly conditional demand data base. In order to reflect the variance in electricity use, high and low load level priors were developed for each end-use based on the standard deviation in load levels estimated for the households in the hourly conditional demand analysis. For each prior, estimates of household square footage and income were also developed based on the standard deviation of these household characteristics in the survey data used in the hourly conditional demand analysis.

The distribution of annual end-use electricity consumption across the 8,760 hours in the year was calculated for each of the fifteen end-uses using the load shape representations developed in an earlier study utilizing residential end-use metered data from the same service territory on which the hourly conditional demand analysis was performed (Blaney 1992). The end-use metered data were collected for the period April 1986 throughout March 1987.

Model Specification

The objective of this conditional demand analysis was to develop estimates of typical hourly electricity use for residential households by appliance end-use categories. To this end, a statistical model was developed in which total hourly household electricity use was specified to be a function of the stock of electric end-use appliances and household physical and demographic characteristics. The general specification of the CDA model is given by the following equation:

$$L_{it} = \sum_{j=1}^{J} f_{jt}(X_{ijt}) * D_{ijt} + e_{it} \qquad (2)$$

Where:

L_{it} = Electricity consumption in household i in period t

X_{ijt} = Variables that determine electricity consumption in household i by appliance j in period t

D_{ijt} = 1 if household i has appliance j in period t
= 0 otherwise

e_{it} = error term for household i in period t

In this specification, residential end-use hourly load is estimated as a function of each household's stock of appliances, as denoted by the D_{ijt} in Equation (2). In general, the $f(X_{ijt})$ are specified to consist of factors influencing appliance usage. The fictional relationships used in this analysis for weather-sensitive and non-weather-sensitive end-uses are described below. The purpose of the conditional demand analysis was to estimate the $f(X_{ijt})$'s in Equation (2), which determine the hourly electricity usage for each household appliance.

End-Uses

Functional forms, $f(X_{ijt})$'s in Equation (2), were included in the conditional demand analysis for the fifteen end-uses listed in Table 1. The saturation levels for each of these end-uses is also listed in Table 1.

Specification for Weather-Sensitive End-Uses

The fictional form of the conditional demand analysis specification for weather sensitive end-uses can be illustrated using electric space heating as an example, as presented in Equation (3):

$$\begin{aligned} H_{it} = (&B1*SQFT_i*ON_{it} \\ &+ B2*SQFT_i*ON_{it}*MILD_{it} \\ &+ C1*SQFT_i*ON_{it}*BACKUP_i \\ &+ D1*SQFT_i*INCOME_i*ON_{it})*HEAT_i \end{aligned} \qquad (3)$$

Table 1. Appliance End-Uses and Saturation Levels

Appliance	Saturation
1. Electric Baseboard & Forced Air Heating	66.1
2. Electric Heat Pumps	5.1
3. Hot Water Heaters	56.5
4. Central Air Conditioners	13.6
5. Heat Pump Cooling	7.7
6. Room Air Conditioners	26.4
7. Ranges	78.9
8. Second Refrigerators	
9. Freezers	63.0
10. Microwave Ovens	93.1
11. Dishwashers	70.1
12. Clothes Washers	95.7
13. Clothes Dryers	85.6
14. Electric Portable Heater	15.5
15. Miscellaneous	100.0

Where:

H_{it} = Electricity use for space heating in household i in period t
$SQFT_i$ = Square footage for household i
$INCOME_i$ = Income for household i
$BACKUP_i$ = 1 if household i has a non-electric backup space heating source
= 0 otherwise
ON_{it} = 1 if this is the first or second observation for household i in period t (i.e., space heating is on)
= 0 otherwise
$MILD_{it}$ = 1 if this is the second observation for household i (i.e., observations for the mild temperature segment)
= 0 otherwise
$HEAT_i$ = 1 if household i has electric baseboard or resistance space heating
= 0 otherwise

In this specification, the dummy variable ON indicates that this observation corresponds to the estimated household electricity use at a temperature that is cold enough for the space heater to be operating. These observations are represented as L1 and L2 in Figure 1 above. Similarly, the dummy variable MILD indicates that this observation corresponds to the estimated household electricity use at a relatively mild temperature, but one at which the space heater is still operating. This observation is represented as L2 in Figure 1 above.

In addition to electric baseboard and resistance heating, electricity use for heat pump space heating, heat pump cooling, and central air conditioning were estimated as a function of household square footage and income levels using functional forms similar to Equation (3). A simpler functional form was used for portable heaters and room air conditioners. Electricity use for these end-uses was estimated simply as a function of the dummy variables ON and MILD .

Specification for Non-Weather-Sensitive End-Uses

For the non-weather-sensitive end-uses electricity use was specified to be a function of the log of the number of household members. For the miscellaneous end-use, electricity use was estimated to be a function of square footage and the type of household—single family or multi-family.

Model Estimation

The conditional demand analysis specification was estimated twice for each of the 24 hours in the eight season and day-type categories. In the first estimation process, the specification was estimated using ordinary least squares and excluding the Bayesian priors. This initial estimation was undertaken to determine to what extent reasonable hourly load profiles could be estimated for the fifteen end-uses without the use of priors.

In the second estimation process, the Bayesian priors were incorporated using a weighted least squares approach. In this second estimation, equal weights were applied to the actual observations and the Bayesian priors for all but one appliance. Relative weights of 10-to-1 were placed on the Bayesian priors for the miscellaneous end-use because of the inability of the least squares model to estimate a load shape for this end-use category.

Results

In general, the ordinary least square estimated coefficients were statistically significant and had the right sign for the electric space heating and air conditioning end-uses. However, ordinary least squares was not able to estimate reasonable results for non-weather sensitive end-uses that were confounded. For example, clothes washers, which had a saturation of 95.7 percent, and microwave ovens, which had a saturation of 93.1 percent were confounded.

For these high saturation non-weather-sensitive end-uses, the incorporation of the Bayesian priors in the weighted least squares estimation greatly improved the estimated load shapes.

The effect of the priors on the final estimated coefficients depended on the strength of the correlation between the actual observations on total household electricity use and the explanatory variables, the $f(X_{ijt})$'s in Equation (2). For example, if there was a strong correlation between total household hourly electricity use and the number of household members for households with electric water heaters, then the effect of incorporating the Bayesian priors on the estimated coefficients for this end-use and the resulting load profiles was minimal.

Figure 2 presents the estimated total electricity use load shape for a representative household for a typical cold winter weekday. Three load shapes are presented: the ordinary least squares estimate; the Bayesian prior developed from the annual conditional demand analysis and the end-use metered load shapes; and the weighted least squares estimate incorporating the Bayesian priors.

There is relatively close agreement among the three estimated total household load shapes. The least squares estimates are higher than the Bayesian priors in all hours except the early morning hours. As expected, the weighted least squares estimates are between the least squares and Bayesian priors in all hours.

Figure 3 presents the results of the least squares and the Bayesian prior weight least squares estimation process for electric space heating on cold winter weekdays. In most hours the least squares estimation for electric space heating yielded coefficients that had the right sign and were statistically significant at the 95 percent confidence level. As Figure 3 demonstrates, the space heating load estimates resulting from the least squares estimation had a typical space heating shape with a peak in the early morning hours and a secondary peak in the evening hours.

Figure 3 also demonstrates the effect of incorporating the Bayesian priors on the space heating load shape. Incorporation of the priors had little effect on the estimated coefficients and resulting load shape in the peak morning hours, the afternoon hours in which space heating electricity use is typically at its lowest levels, and at the peak evening hours. However, inclusion of the priors tended to raise the estimated space heating load levels substantially in the early morning hours.

Figure 4 presents similar results for microwave ovens. In this case, the ordinary least squares estimates had a typical load shape for cooking end-uses with sharp spikes in the morning breakfast hours and evening dinner hours. The least squares estimates also indicate a large jump in electricity use in microwave ovens at 10 pm as well. While the least squares estimates for microwave ovens have a typical pattern for cooking end-uses, they are unreasonably high in magnitude.

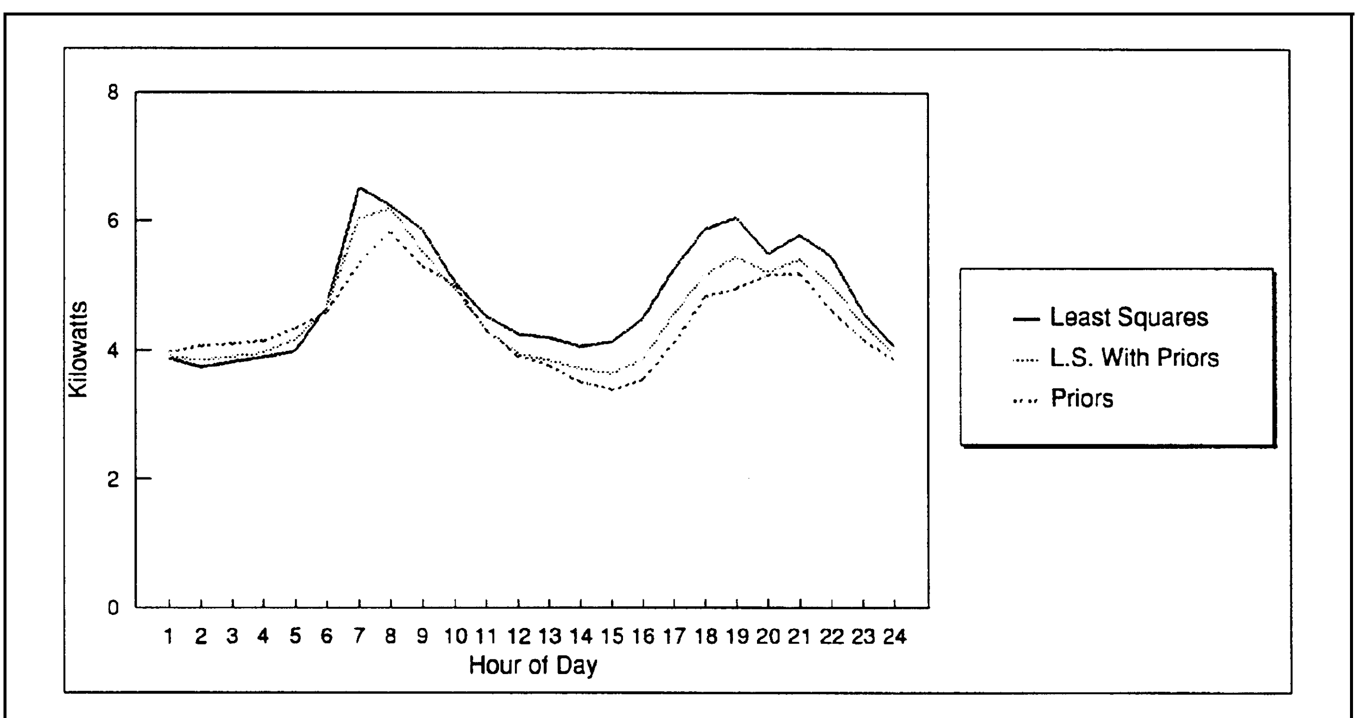

Figure 2. Estimated Total Household Load Shapes for a Winter Weekday

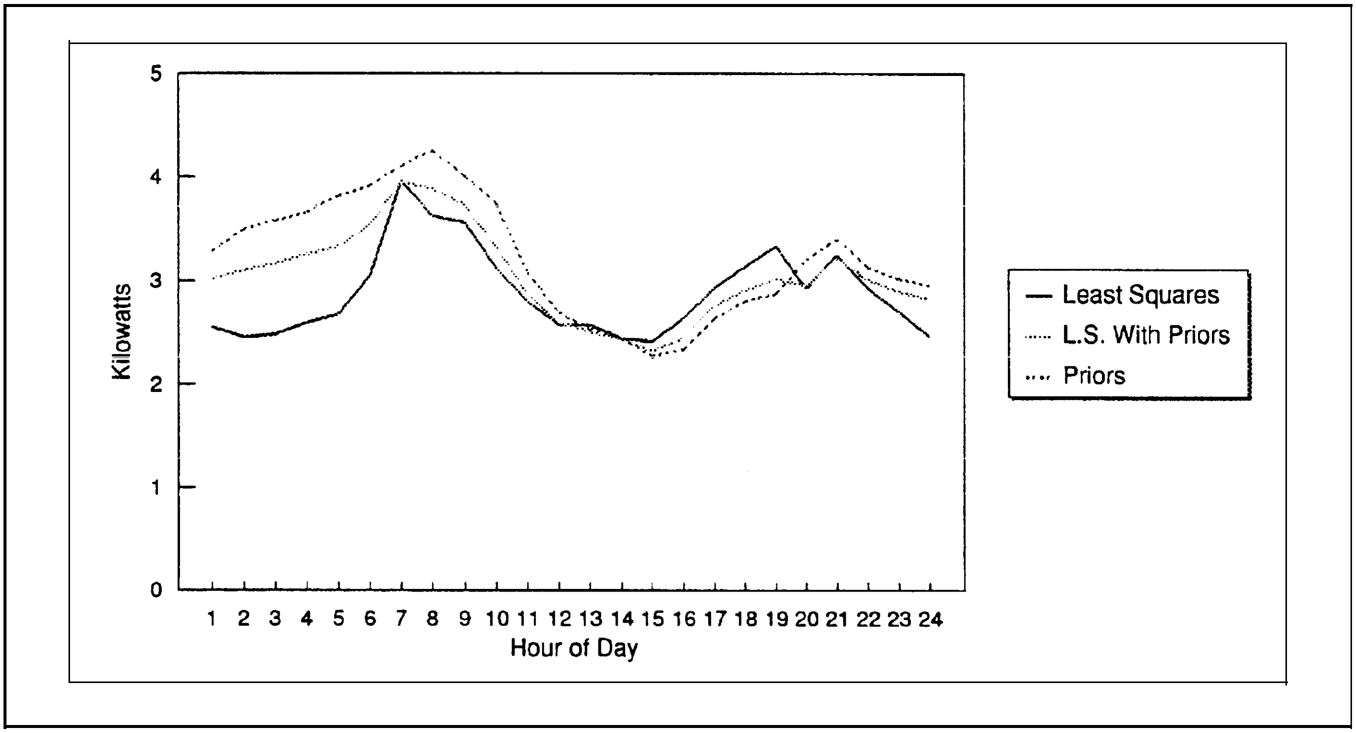

Figure 3. Estimated Electric Space Heating Load Shapes for a Winter Weekday

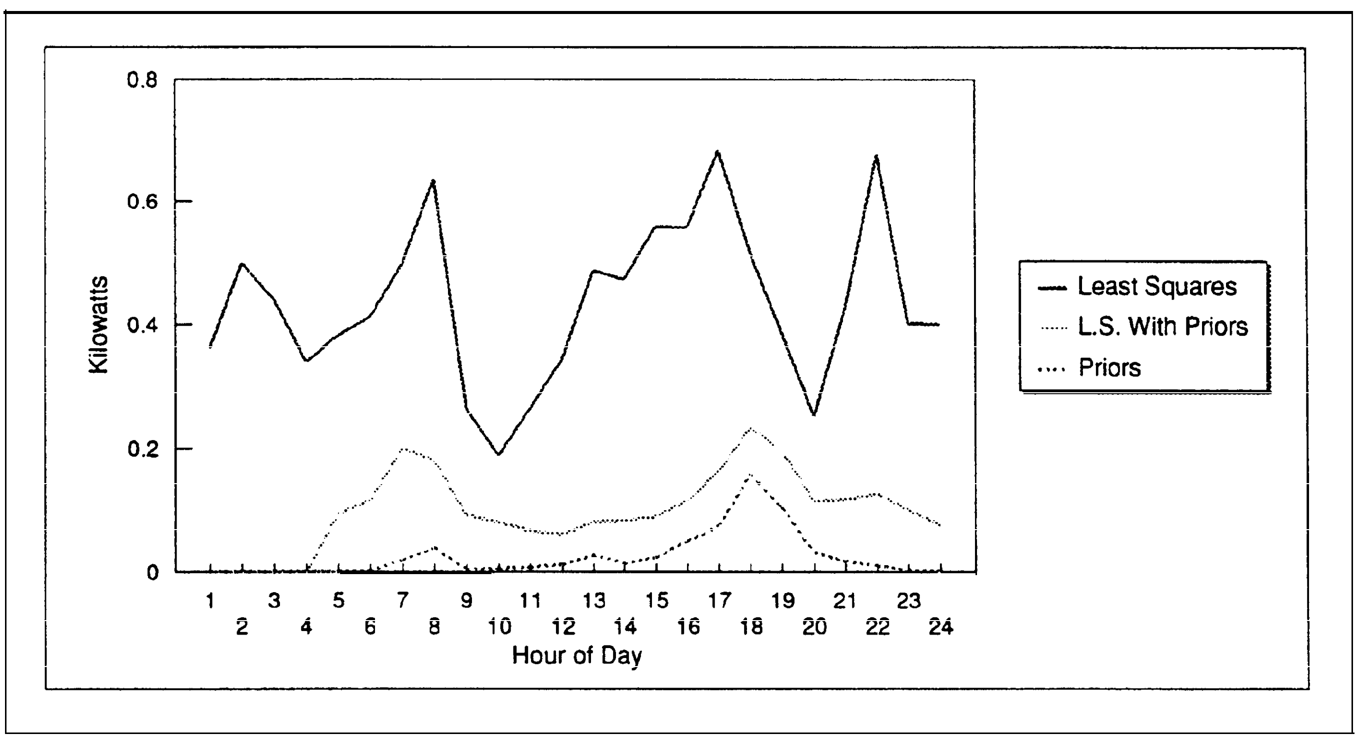

Figure 4. Estimated Microwave Oven Load Shapes for Winter Weekdays

The ordinary least squares overestimation of electricity use in microwave ovens is indicated in Figure 4 by the large gap in magnitude between the least squares estimates and the Bayesian priors. However, incorporation of the Bayesian priors in the weighted least squares estimation yields a load shape that is much closer to the Bayesian priors than the least squares results.

Figure 5 demonstrates the usefulness of the conditional demand analysis results for estimating load shapes profiles

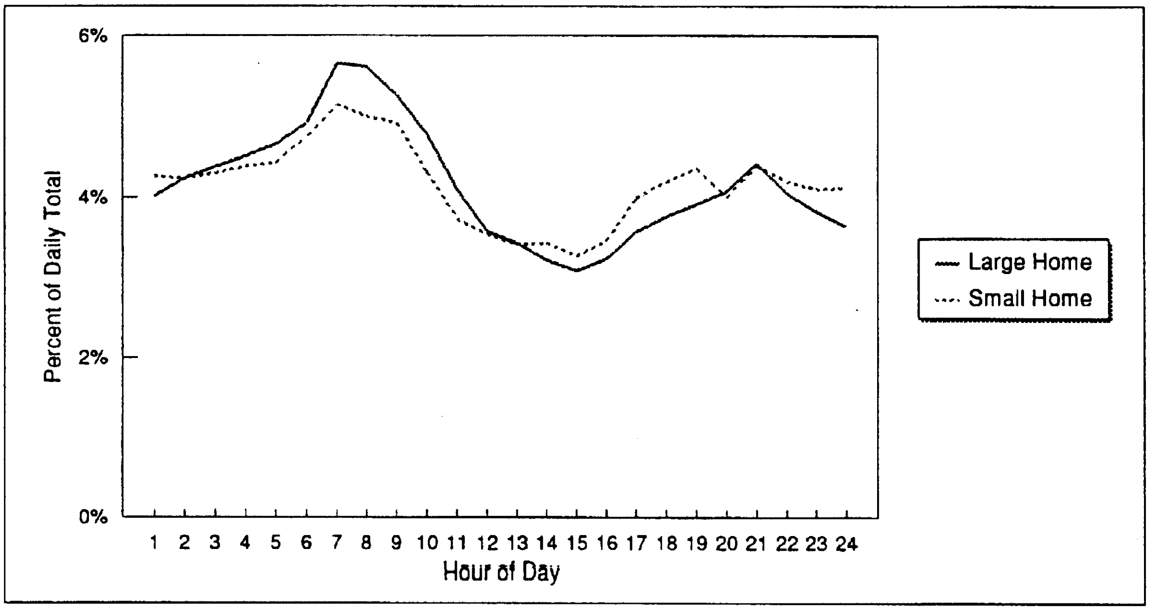

Figure 5. Estimated Load Profiles for Large and Small Households for Winter Weekdays

for households with different physical and demographic characteristics. The estimated electric space heating load shape profiles for two different household types are shown in Figure 5. Household 1 is a large household with total square footage of 2,600 and a high income of $80,600. In contrast, Household 2 is much smaller with square footage of 900 and income of $17,200.

These results indicate that small, low income households tend to have flatter electric space heating load profiles than larger households with higher incomes. These results could be useful in analyzing DSM load programs for electric space heating.

Finally, Figure 6 illustrates the substantial effect that weather can have on hourly load levels in weather-sensitive end-uses. The estimated hourly load levels for electric space heating for a typical cold winter weekday are nearly twice as high as the load levels on mild days. Most conditional demand analyses done to date have ignored this powerful weather effect.

Acknowledgments

The work documented in this report was conducted for the Niagara Power Mohawk Corporation. The opinions, findings, and conclusions expressed herein are solely those of the author and do not necessarily reflect the view of Niagara Mohawk Power Corporation.

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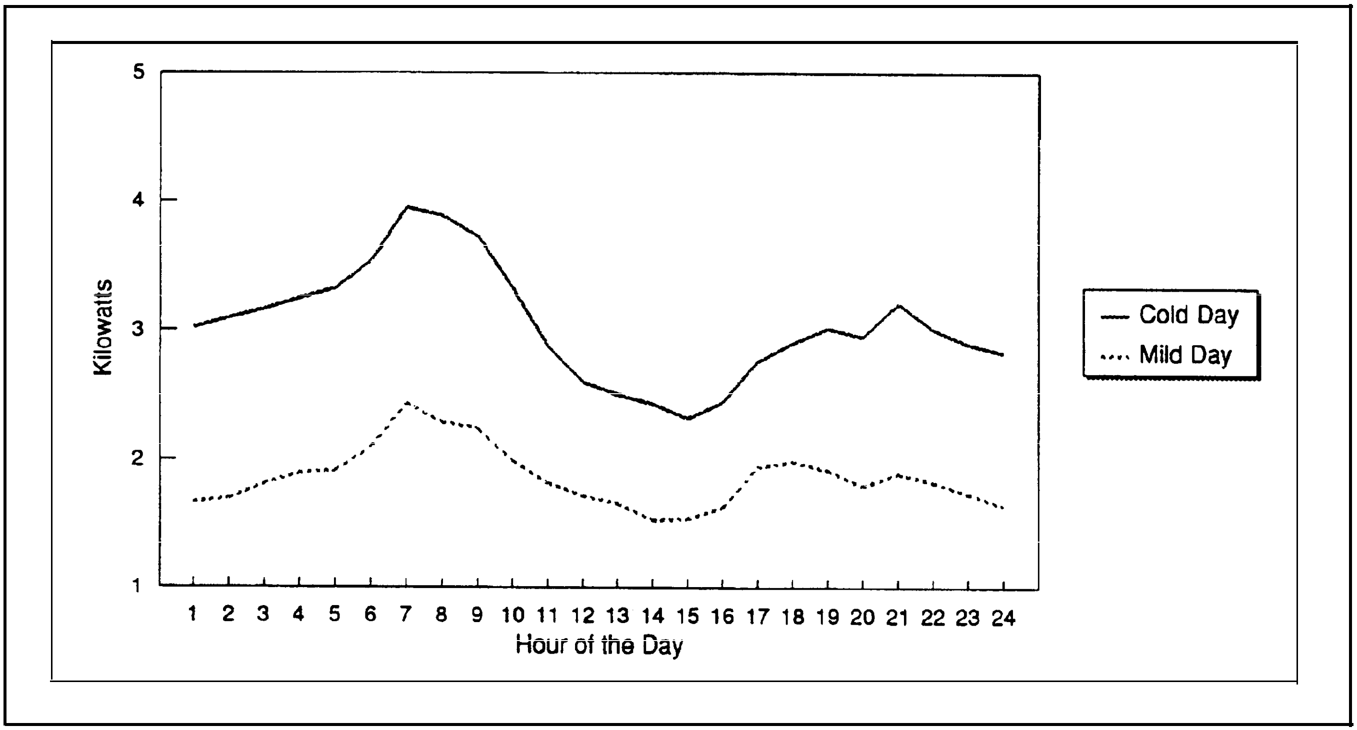

Figure 6. Effect of Temperature on Estimated Load Shapes for Electric Space Heating