INTEGRATED LOAD AND TIME OF DAY MODELS FOR ELECTRICITY IN RESIDENCES

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ABSTRACT

This paper applies Thermodynamic Behavioral Integration (TBI) modeling to electricity consumption in the residential sector in the Nevada Power area. TBI uses conditional demand techniques to integrate thermodynamic and behavioral models. A crucial aspect of the integrated model is explicit incorporation of feedbacks between the engineering and economic components. For example, consumer choice of thermostat setting is affected by the price of raising the interior temperature by a degree, which in turn, depends on the thermal tightness of the house. Overall price and income elasticities are computed. The perverse price effect (conservation tends to make warmth cheaper and therefore tends to increase consumption) is naturally included in this structure. This technique has been applied to modeling residential electric consumption, commercial electric consumption, and industrial gas consumption with excellent results.

In this paper, TBI is used to generate a single model incorporating both monthly and time of day consumption for space heating, space cooling, water heating, pool pumping and unspecified. The data set included whole house consumption at both the hourly and monthly levels. It also included end use metering for space cooling and some other end uses. The goal was to use TBI to exploit all levels of data in calibrating a model for both monthly and time of day consumption. In effect, the process involves mixing the end use metering data with the whole house data as well as mixing the monthly and hourly data. Results are given at both the hourly and monthly levels for consumption by each end use.

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I. INTRODUCTION

This paper investigates the consumption of electricity by residential customers in the Nevada Power Company(NPC) service territory (Las Vegas NV). Thermodynamic Behavioral Integration (TBI), a modification of the Conditional Demand technique [5] is used to estimate hourly and monthly end-use electricity demand equations. These equations are, in turn, used to estimate end-use load shapes and annual energy consumption. TBI has been applied to modeling residential electric consumption[1,2], commercial electric consumption[3], and industrial gas consumption[4] with excellent results.

Three innovations in the conditional demand estimation procedure were developed in this work. First, the hourly (and monthly) estimates of space conditioning appliance usage were based upon a detailed model in which the relevant thermodynamic relationships were integrated with an economic model in which consumer energy-related decisions are based upon variables such as prices and income and other relevant variables. The purpose of this procedure is to increase the accuracy of our estimated model and to take into account the effects of variables such as insulation which have a direct effect on the reduction of consumption but may also have an indirect effect on consumption by altering the behavior (e.g. thermostat settings) of consumers. Second, a mixed time scale estimation procedure was used to assure logical consistency between the hourly and annual energy use estimates. Third, a procedure was used to combine, optimally, end use and whole house metering to increase the precision of appliance load shapes.

In the remaining sections, we discuss important theoretical issues, state the estimation equation, give econometric goodness of fit information, and describe the data set used in the analysis. Finally, we report the estimated residential end-use energy consumption, and the hourly load shapes for a set of residential appliances.

II. THE ESTIMATION DATA SET

The Sources of Data

The data set for this study was constructed from three separate, but related, data sets: 1)general residential (GR), 2)PURPA, and 3)Load Management (LM). The appliance and other household information for customers in these data sets is based upon a common survey instrument. The data sets also share a common weather data base. GR contains survey information and monthly consumption over two years for approximately 2700 households. PURPA and the LM are disjoint subsets of GR. They both contain hourly consumption figures (1984) for the whole house. LM also contains metered consumption through selected appliances such as central air-conditioners, electric water heaters and pool pumps.

Construction of the Estimation Data Set

A pooled data set of practical size was made from subsets of PURPA and LM. Also included was a subset of GR, (NONPLM), containing neither PURPA or LM customers. In all, 12140 observations were used in the estimation of the regression coefficients, of which 1008 were monthly and 11132 were hourly observations. Of the total observations, 10918 were from LM (10419 hourly, 499 monthly), 745 were from PURPA (713 hourly, 32 monthly), and 477 were from NONPLM (all monthly).

The final data set contained 12066 single-family observations (11086 hourly, 980 monthly) and 74 multi-family observations (46 hourly, 28 monthly). The primary objective of this study was to estimate appliance specific hourly load shapes, hence the dominance of hourly observations in the estimation data set. The scarcity of multi-family observations in the hourly analysis is due to missing answers on surveys from multi-family customers.

Although we favored the LM data in creating the estimation data set, the conditional mean values used in computing the hourly load shapes and the annual average energy consumption were taken from both the general residential data set and an hourly weather data set. The former data set has been shown in a previous analysis (by Mr. Harris Lee of NPC) to be a reasonable representation of the NPC residential customer class. Actual construction of the data set is explained in [6].

III. THEORETICAL ISSUES

III.1 The Integrated Thermodynamic/Economic Model

Both an hourly and a monthly thermodynamic model were constructed for each end use. The hourly model for central air conditioning is based in the thermal network in Figure 11 and results in a difference equation of the form[1]:

$$BUCENTAC_t = f(BUCENTAC_{t-1}, CDH_t, CDH_{t-1}, IG_t, IG_{t-1}, Z.LATENT_t, SUN_{t-1}, U1, U2, S), \quad (1)$$

where

[1] Hourly models begin with the diffusion equation and result in a difference equation for the temperature of the energy storage devices and an algebraic equation for the backup consumption as a function of the storage temperature and other variables [7]. These were then converted to a difference equation in the hourly backup.

$BUCENTAC_t$ is the air conditioner consumption for hour t (Btu/hr),
CDH_t are the cooling degree hours for hour t,
IG_t is the internal heat gain from other appliances and persons in the household for hour t (Btu/hr),
$Z.LATENT_t$ is the latent load for hour t,
SUN_t represents the solar insolation for hour t (Btu/hr),
U1 and U2 are functions (Btu/hr-deg F) of the characteristics of the house (see Figure 1), and
S is the thermal storage capacity (Btu/deg-F) of the house.

Models for space heating and air-conditioner/evaporative cooler are similar. Models for other appliances are discussed in Section IV. The monthly equation is simply the integral of the hourly equations over the hours of the month. Decision variables were identified in the hourly (and hence monthly) models, and these were modeled as functions of engineering parameters, marginal electricity price and income. The result is an integrated model producing hourly and monthly estimates of electricity consumption by end use. This model contains strategically placed adjustment coefficients which are simultaneously econometrically calibrated.

III.2. The Mixed Time Scale Estimation Procedure

Our objective has been to estimate models of hourly and monthly energy use that would be useful for forecasting and market assessment. The mixed frequency procedure ensures that such hourly and monthly models are logically consistent with each other. It permits combining hourly and monthly (or annual) sales data in order to simultaneously estimate the related parameters of demand equations for hourly and monthly electricity usage. The primary advantage of this new procedure is to buttress samples of expensive hourly metered residential data with more readily available and less expensive monthly billing data. This type of combined data set can more accurately estimate parameters of logically consistent monthly and hourly residential energy demand equations.

The Elements of the Procedure

The procedure makes use of a merged sample containing _monthly_ sales, weather and survey data with corresponding information on a sample of _hourly_ consumption. The two samples may contain information on different sets of customers. However, the customers in the two samples should be classifiable into similar analytical categories; e.g., commercial building-types or residential building-types (single- or multi-family).

The basic idea is to exploit the fact that monthly consumption is simply the sum of the hourly consumptions occurring in that month. Of course, this holds for each end-use as well as the total household use. Generally, the monthly parameters can be written as weighted sums of the time-of-day parameters. In order to avoid heteroskedasticity, one must also correct for the fact that monthly and hourly observations have different variances.

Technical Aspects of the Procedure

Monthly electricity consumption can be expressed as the sum of the separate hourly consumption magnitudes; i.e.,

$$E_m = \sum_{d=1}^{BD} \sum_{t=1}^{24} (E_{dt}) \tag{2}$$

where E_m is monthly billed consumption
d is an index indicating the day
BD is the number of days in the billing month
E_{dt} is consumption in hour t of day d.

For simplicity, we suppress reference to the end-use disaggregation inherent in our analysis. The final estimation equation contains such detail.

In the merged sample, the dependent variable would be either monthly, E_m, or hourly consumption, E_{dt}. The goal is to estimate the parameters of demand functions for hourly and monthly uses, which would then be used to compute estimates of hourly and monthly loads, E'_{dt} and E'_m, respectively. The actual monthly and hourly consumption levels can each be expressed as the sums of a predicted level and an error. That is,

$$E_m = E'_m + U_m \tag{3}$$

and

$$E_{dt} = E'_{dt} + U_{dt} \tag{4}$$

where U_m is the error in predicting monthly consumption, and U_{dt} is the error in predicting hourly consumption. The procedure exploits information about 1)the relationships between the parameters of the equations used to predict E'_m and E'_{dt}, and 2)information about the distributions of the errors, U_m and U_{dt}.

Parameter Relationships

The idea is to exploit information assuring logical consistency between the hourly and monthly demand equation parameters. There are several possible types of relationships between the hourly and monthly parameters depending upon the type of associated variable. For example, insulation values do not change between hourly and monthly models. Similarly, daily thermostat setting patterns such as night setback etc vary with repetitive patterns. One could also easily handle variations over the days of the week.

Thus, as expected, some hourly information is necessary to estimate parameters with true hourly variation, but only monthly summary information is necessary to estimate their sum or to estimate parameters which do not vary by the time of day. This property is at the root of the use of the mixed time scale procedure to specify logically correct parameter constraints which can be used to increase the efficiency of the estimation procedure. Furthermore, note that even in a case in which a coefficient varies hourly, the number of estimated parameters and the previously mentioned multicollinearity problem can be considerably reduced by modeling the form of the hourly variation.

Time-of-Day Coefficient Modeling

Modeling the hourly parameters can result in a considerable reduction in the number of parameters to be estimated. This can have the dual benefits of increasing the degrees of freedom and reducing multicollinearity. Water heater and pool pump models as well as those for unspecified appliance consumption were modeled using linear (pool pump) or quadratic splines (all others). The spline knots (end points) were determined by trial and error from the end use metered data. The current procedure allows for end-point equality or zero restrictions. Of course, the degree of the spline can be changed (tested) to suit the form appropriate for a given data set.

The Variance of the Error Term

A generalized least squares (GLS) procedure can be used to optimally weight the observations in our combined sample. If the variances of the U_{dt} are equal to a constant k and, for the moment ignoring the cross error covariances, the variance of the error term, VAR(U), is:

$$VAR(U) = k(H) + k(BD)(24)(1-H). \tag{5}$$

Employing a Generalized Least Squares (GLS) approach with weighting, W, equal to:

$$W = (VAR(U)/k)^{1/2} \tag{6}$$

results in the GLS estimating equation

$$\begin{aligned} E/W &= E'_{dt}\,[H/W] + E'_{m}\,[(1-H)/W] \\ &\quad + U_{dt}\,[H/W] + U_{m}\,[(1-H)/W] \end{aligned} \tag{7}$$

Now the variance of the error terms is constant across observations. In practical terms, this weighting procedure would result in a higher weighting for the hourly observations than for the monthly observations. Furthermore, the weights given monthly observations decline as the number of days in the billing period increase.

The above discussion has been simplified for exposition. The GLS procedure used in our actual estimation was extended to take account of such things as appliance stock differences across our sample and pooling. Conditional Demand estimation results in heteroscedasticity in the error structure since we can regard each end-use demand equation present in the household as contributing to the error. Since different households have different configurations of appliances, non-constant error variances can be expected to result.

IV. THE REGRESSION EQUATION AND THE DERIVATION OF THE END-USE CONSUMPTION ESTIMATES

Energy use is estimated from the estimated coefficients of the overall Conditional Demand regression equation and the characteristics of the NPC residential customers. The conditional demand equation is a compact way to account for appliance-specific (conditional) demand equations and their sum.

The estimated regression coefficients are logically consistent with either hourly or monthly observations. Hence, to estimate the monthly UEC[2] for a particular appliance, we apply the relevant estimated coefficients to the monthly means of the explanatory variables for that appliance. On the other hand, if we want to estimate the UEC for a particular hour, we apply the same coefficients to the hourly means of the explanatory variables for that appliance. To simplify the presentation of the individual end-use UEC calculations, the estimated coefficients of the overall Conditional Demand equation are reported by end-use category. The R^2 of the overall regression equation is 0.79.

In the discussion of these results we denote the conditional mean of a variable by the variable name followed by a single quote. Preceeding each such term is its estimated coefficient whose t ratio is given in parentheses immediately below. Note that significant t ratios exceed 2 in magnitude. The hourly load shapes reported in section V are calculated in a similar fashion, except that, the conditional means of the variables for specific hours were used.

<u>The Central Air-Conditioner</u>

hourly load:

$$UECcentac_t = \underset{(7.22)}{.8022} * (BUCENTAC_t') + \underset{(3.79)}{.112} * (INCOMETERM_t')$$

$$- \underset{(-4.57)}{.1359} * (PRICETERM_t') - \underset{(-5.54)}{.204} * (MF * BUCENTAC_t') , \qquad (8)$$

where $INCOMETERM_t'$ and $PRICETERM_t'$ incorporate[6] the conditional means of income and price, respectively. The t subscript refers to an hourly observation. Note that the expression ($MF*BUCENTAC_t$) is a decremental term to allow for lower consumption in multi-family units since MF equals 1 only for multi-family family homes. The t-ratios for the coefficients are given in parentheses below the estimated coefficients. For example, substituting the hourly conditional mean variables for eight A.M., for the billing months June through August (1984), the eight A.M. central air- conditioning load for the average residential customer is:

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2 The UEC is the average electricity consumption in a given period assuming the appliance is present in the home. Here, the average is over all households having the appliance. Hourly, monthly and annual UEC's were computed in the study.

$$UECcentac_{8am} = .8022*(2551.4) + .112*(3368.3) - .1359*(3134.3) - .204*(247.6) = 1946.3 \text{ BTU's}.$$

Similar calculations are used in obtaining the system-level load-shape plots shown in section V of this paper. These calculations are done for all the hours of the day to obtain the load shapes shown in that section. Because of the volume of such calculations (24 multiplied by the number of end-uses) we present each estimated equation only at the annual level. To compute the monthly consumption levels, substitute the average monthly conditional mean values into the demand equations and divide the resulting estimated annual consumption by 12.

<u>The Combination Central Air-Conditioner/Evaporative Cooler</u>

annual:

$$UECcombo = 12 * (\underset{(7.22)}{.8022}*(BUCOMBO_m') + \underset{(3.79)}{.112}*(INCOMETERM_m') - \underset{(-4.57)}{.1359}*(PRICETERM_m') - \underset{(-5.54)}{.204}*(MF*BUCOMBO_m')) \quad (9)$$

<u>The Electric Space Heater</u>

annual:

$$\underline{UECeheat} = 12 * (\underset{(17.72)}{1.0021}*(BUEHEAT_m') + \underset{(3.79)}{.112}*(INCOMETERM_m') - \underset{(-4.57)}{.1359}*(PRICETERM_m') - \underset{(-5.54)}{.204}*(MF*BUEHEAT_m')) \quad (10)$$

<u>The Freezer</u>

annual:

$$\underline{UECfreezer} = 12 * (\underset{(5.52)}{1.0072} * (BUFREEZER_m')) \quad (11)$$

<u>Additional Refrigerators</u>

annual:

$$\underline{UECaddref} = 12 * (\underset{(5.52)}{1.0072} * (BUADDREF_m')) \quad (12)$$

<u>The Water Heater</u>

annual:

$$\underline{UECewh} = 12 * \{ (1 - \underset{(-5.54)}{.204} *MF) * [\underset{(5.36)}{533.5866} * (EWHCON_m'))$$
$$- \underset{(-.77)}{65.6075}*(EWHNH1_m') + \underset{(1.60)}{21.986}*(EWHNH2_m') - \underset{(-2.17)}{64.8286}* (EWHNH2D6_m')$$
$$+ \underset{(2.41)}{58.7012}*(EWHNH2D10_m') - \underset{(-1.60)}{30.4583} * (EWHNH2D17_m')]$$
$$+ \underset{(3.79)}{.112} * * (INCOMETERM_m') - \underset{(4.57)}{.1359} * (PRICETERM_m') \} \quad (13)$$

where

EWHCON = 1 if hourly, 24*BD if monthly observation;
EWHNH1 = PER*t if hourly, PER*(24*25/2*BD if monthly;
EWHNH2 = PER*t^2 if hourly, PER*(24*25*49/6)*BD if monthly;
EWHNH2D6 = PER*(DUM6*(t-6)^2) if hourly,
= PER*(18*19*37/6)*BD if monthly observation;
EWHNH2d10 = PER*(DUM10*(t-10)^2) if hourly,
= PER*(14*15*29/6)*BD if monthly observation;
EWHNH2D17 = PER*(DUM17*(t-17)^2) if hourly,
= PER*(7*8*15/6)*BD if monthly observation;
INCOMETERM = INCN if hourly, INCN*24*BD if monthly;
INCN = income divided by average income;
PRICETERM = MPRN if hourly, MPRN*24*BD if monthly;
MPRN = marginal price divided by average marginal price;
PER = number of people in the house;
DUM6 = 1 if hour > 6, zero otherwise;
DUM10 = 1 if hour > 10, zero otherwise;
DUM17 = 1 if hour > 17, zero otherwise; and
BU___ is the TBI equation for end use ___.

Pool Pumps

annual:
$$UECpool = 12 * \{ \underset{(.52)}{295.6568} * (POOLCON_m') + \underset{(2.34)}{290.2363} * (POOLH1D6_m') - \underset{(-2.16)}{637.4512} * (POOLH1D16_m') + \underset{(3.79)}{.112} * (INCOMETERM_m') - \underset{(-4.57)}{.1359} * (PRICETERM_m') \} , \quad (14)$$

where POOLH1D6 = DUM6*(t-6) if hourly, (18*19/2)*BD if monthly;
POOLH1d16 = DUM16*(t-16) if hourly, (8*9/2)*BD if monthly;

Unspecified Energy Use

annual:
$$\underline{UECunspec} = 12 * \{ (1 - \underset{(-5.54)}{.359} * MF) * (BUUNS_m') + \underset{(3.79)}{.112} * (INCOMETERM_m') - \underset{(-4.57)}{.1359} * (PRICETERM_m') \} \quad (15)$$

The coefficient .359 yields a decrement of consumption for multi- family units. $BUUNS_m$' is the integral of $BUUNS_t$' which is a quadratic spline. Thus, estimation of the UECs required the following steps: 1)specify appliance-specific Conditional Demand functions for each of the appliances; 2)add all the conditional demand functions to obtain the overall regression equation; 3)estimate the coefficients of this regression equation; 4)calculate the conditional means of the explanatory variables in the regression equation; and 5)substitute the relevant estimated coefficients and conditional means into each of the appliance-specific demand functions to estimate the UECs for each of the specified appliances. Note that the hourly load shapes were derived using the same equations as those used to compute the yearly UECs.

V. THE PRIMARY RESULTS OF THE STUDY

V.1. Estimated Annual Residential End-Use Consumption in the Nevada Power Co. Service Territory.

The annual Unit Energy Consumption (UEC) for each of the eight appliances was computed from the estimation equations. Average energy use per household in the corresponding appliance category equals the product of these UEC's and the corresponding saturation. Total electricity used in each appliance category is the previous product multiplied by the number of customers in the service territory. These products are then summed to obtain an estimate of the average consumption per customer in the NPC service territory using the identity

$$E' = \underset{i}{\mathrm{SUM}}\, [UEC_i * SR_i] \tag{16}$$

where E' is average annual electricity consumption per customer;
UEC_i is average annual electricity consumption through appliance i (for those customers who have it);
SR_i is the saturation rate for appliance i; and
$\underset{i}{\mathrm{SUM}}$ denotes the sum over i.

Results for single family and multi-family homes are given in Tables I and II. The estimated single-family consumption is within 98.95% of the actual level, while estimated average consumption for multi-family households is 7.66% higher than the actual average consumption.

V.2. Estimated End-Use Load Shapes

In this section we present the daily load shapes (in BTU/hr) for five appliance categories[3] estimated from our conditional demand equations. The system-level load shapes for air-conditioning, space heating, electric water heating, pool pumping and whole house consumption appear in Figures 2-4. Figures 5-7 contain comparisons between estimated and actual average load shapes for air conditioning, water heating and pool pumping for customers in the LM sample (end use metering). Note that estimates of load shape for this sample are different from those at the system level because of the difference between the characteristics of the load-management customers and other Nevada Power Company customers. In general, the Load-Management customers consume

[3] air conditioning, space heating, water heating, pool pumping, the whole house load shape.

more air-conditioning because they live in larger houses and have higher incomes than the average Nevada Power Company customer.

V.3. Price and Income Elasticities

The estimated overall price and income elasticities are:
Income Elasticity = 0.112; Price elasticity = -0.136.

VI. SUMMARY

The procedure outlined here can economize on data when estimating hourly electricity demand equations and can insure that estimated hourly and monthly electricity demand equations are logically consistent with each other. Furthermore, the technique is applicable to problems in the commercial and industrial sectors.

There are four main advantages to the use of this new procedure:

1. It economizes on the requirements for expensive hourly observations when trying to improve the accuracy of time-of-day demand parameters. Using this new procedure, relatively cheap monthly observations may be used to buttress analyses which employ relatively expensive hourly observations.

2. It guarantees that demand equations for time-of-day and monthly energy usage will be logically consistent with each other - both in predicting energy usage itself and on the theoretical level.

3. It will aid in improving the transferability of energy sales equations from one region to another since it makes more explicit the linkage between the time-of-day and monthly variables and parameters.

4. The technique can also be applied to save money and/or increase the accuracy of analyses of energy demand for customer types other than residential.

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Table I: Annual Results for single-family Homes. UEC denotes average Unit Energy Consumption assuming the appliance is present, SR denotes saturation ratio for the appliance, and UEC*SR represents the average consumption for the appliance per household.

Appliance	ANNUAL UEC	SR	UEC*SR
Cen. Air Conditioner	4170	.81	3378
Evaporative Cooler & Cen. a/c	2743	.09	247
Electric Space Heater	3966	.50	1983
Water Heater	3606	.41	1478
Freezer	1044	.40	418
Additional Refrigerator	1653	.27	446
Pool	3451	.29	1001
Unspecified	8042	1.00	8042
Total Estimated Consumption per household			16993
Total Recorded Consumption per household			17174

Table II: Results for Multi-Family Homes. UEC denotes Unit energy consumption assuming the appliance is present, SR denotes saturation ratio for the appliance, and UEC*SR represents the average consumption for the appliance per household.

Appliance	ANNUAL UEC	SR	UEC*SR
Cen. Air Conditioner	2212	.83	1836
Evaporative Cooler & Cen. a/c	1668	.03	50
Electric Space Heater	2157	.77	1661
Water Heater	2117	.67	1418
Freezer	1044	.10	104
Additional Refrigerator	1653	.06	99
Pool	3159	.06	190
Unspecified	5085	1.00	5085
Total Estimated Consumption per household			10443
Total Recorded Consumption per household			9700

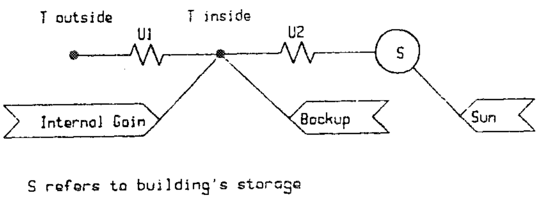

Figure 1: The Thermal Network Model Used in the Hourly Space Conditioning Model.

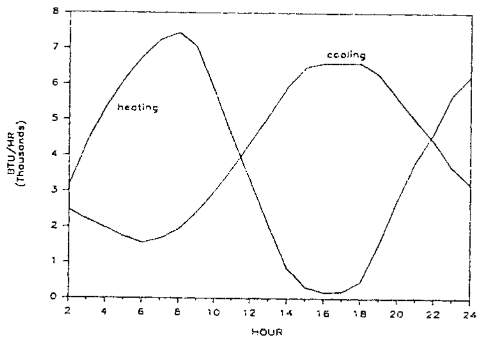

Figure 2: Estimated System-Level Shapes for Summer Cooling (June through September) and Winter Space Heating (January, February, March, November and December).

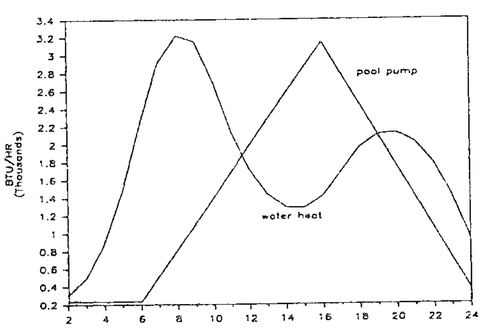

Figure 3: Estimated System-Level Load Shapes for Electric Water Heat and Pool Pumping During all Months of the Year.

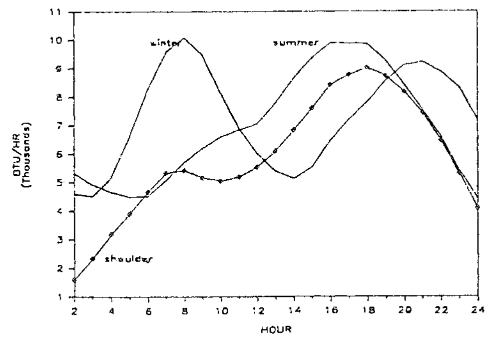

Figure 4: Estimated System-Level Whole House Load Shapes (Btu/hr) for Summer, Winter and Shoulder (Billing Months 4,5 and 10).

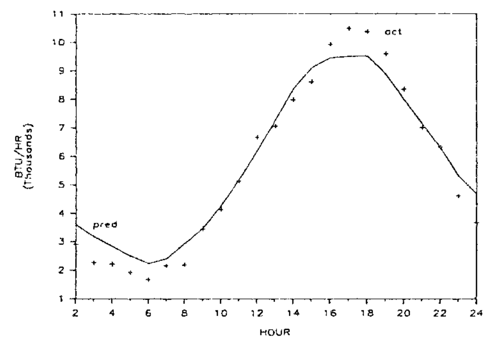

Figure 5: Comparison of Actual and Estimated Average Load Shapes for Air Conditioning (Summer Months; LM data).

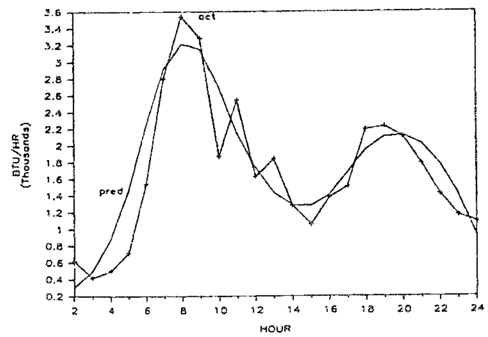

Figure 6: Comparison of Actual and Estimated Average Load Shapes for Electric Water Heating (All Months; LM data).

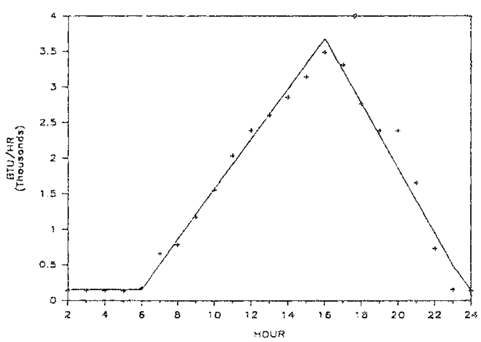

Figure 7: Comparison of Actual and Estimated Average Load Shapes for Pool Pumping (All Months; LM data).