MODELING AND WEATHER-NORMALIZATION OF WHOLE-HOUSE METERED DATA FOR RESIDENTIAL END-USE LOAD SHAPE ESTIMATION

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ABSTRACT

A methodology is presented for modeling load shapes in the residential sector by using hourly whole-house metered data and temperature. Individual household-level load data are analyzed to achieve data smoothing (noise rejection) and compression (in the ratio of approximately 150:1), and to disaggregate the weather-dependent and weather-independent components of the load. The weather-independent (lifestyle) component is modeled as a weighted sum of orthogonal functions (primarily sinusoids and boxcars), while the weather-dependent component is modeled as a non-linear dynamic system based upon thermodynamic principles. Numerical examples show efficient representation of data and good model fit.

I. INTRODUCTION

End-use load shape forecasting plays an important role in the planning efforts of many electric utilities. It provides detailed time-of-use information and a vehicle for evaluating the impact of various types of utility demand-side programs, as well as the changing mix of consumer end-use devices. Such evaluations assume increasing importance as utilities attempt to develop robust planning and rate policies in uncertain economic and regulatory environments and to manage the load on a selective end-use basis in order to achieve efficient operation.

Three methods have been used for developing end-use load shape models: load research, engineering models, and statistical methods.

- *Load research* is the traditional method for determining end-use load shapes. The Edison Electric Institute has compiled appliance use data for many years, and this data base is being expanded by the load research data collected in response to the Public Utilities Regulatory Policy Act (PURPA). Load research data is expensive to collect, validate, and maintain. Its direct use in forecasting presumes that future behavior will be similar to historical patterns, and provides no means for evaluation of changing economic, demographic, or appliance conditions.
- *Engineering models* attempt to construct the load shape from knowledge of the engineering characteristics of appliances and the dwelling in which they are located. These simulation models tend to be complex and expensive to develop, and are based on theoretical considerations that do not reflect the economic and demographic factors influencing load shape. Their use for evaluation of economic or policy issues is minimal.
- *Statistical methods* emerged from the combination of non-causal time series approaches to load shape modeling, and causal econometric analyses of demand. These methods are distinguished by their use of historical data and statistical techniques. They attempt to describe load shapes as functions of economic data, customer and dwelling characteristics, the characteristics of customer appliances, and weather variables.

There is a vast literature drawing upon one or more of these techniques, including the work of Farmer (1963, 1966), Srinivasan and Pronovost (1975), Platt *et al.* (1976), Brice and Jones (1978), Belik *et al.* (1978), Debs and Chong (1979), Simons *et al.* (1979), Belston and Barrager (1979), Nelson *et al.* (1979), Jones and Brice (1979), Utility Modeling Forum (1980), Abu-El-Magd and Sinha (1981), Andrews and McDonald (1981), Broehl (1981), Calloway and Brice (1982), Brice and Pahwa (1982), Brice *et al.* (1982), Ruane (1983), and Walker and Pokoski (1985), who study the modeling and forecasting of load shapes in general, as well as Davis (1958), Galiana and Schweppe (1972), Gupta and Yamada (1972), Corpening *et al.* (1973), Woodard (1974, 1979), Ruane *et al.* (1978), Roy (1981), Pahwa (1983), and Pahwa and Brice (1985) who deal specifically with weather-dependent load shapes.

This paper describes part of a new approach to end-use load shape estimation, integrating these three methods in a single common framework. It accounts for significant causal factors, such as thermal build-up effects and socioeconomic and demographic factors influencing demand. It provides improved parameter estimation through the use of statistically efficient generalizations of conventional regression methods.

Computational efficiency is maintained by integrating engineering and load research data with observations of the load, while decomposing the overall modeling and estimation problem into two levels: *longitudinal time series analysis* models the load shape on a single-house basis, while *cross-sectional analysis* determines the influence of socioeconomic and demographic factors on the load. The former, including modeling and weather-normalization of individual households, is discussed here; the latter is described in a forthcoming paper (Schick, Usoro, Ruane, and Hausman, 1987). The overall approach is presented in greater detail in Usoro, Schick and Ruane (1986).

This method is characterized by low cost, modest data collection needs, explicit causal structure, and a historical basis in both structure and parameter values.

II. GENERAL MODELING METHODOLOGY

Functional relationships between residential end-use loads and household characteristics are sought in order to (i) disaggregate household-level load shapes into end-use (appliance-level) load shapes, and (ii) estimate end-use, household-level, and aggregate (service area) load shapes on the basis of household or service area characteristics. To make the most efficient use of the load shape data, it is useful to represent them by a small set of parameters which must contain most if not all of the relevant information. Since purely random or unpredictable phenomena contribute nothing to the model, they may be eliminated; however, systematic load behavior such as weather-dependence, periodic cycling, or regularly used discretionary loads, must be captured in such a way that they can be reconstructed given only those parameters. In that sense, the parameters may informally be considered *sufficient statistics* for the weather-dependent and weather-independent systematic components of the load shapes.

Some researchers have sought to reduce the dimensionality of the data by data aggregation. However, that method has potential shortcomings: for instance, averaging across days may yield typical hour-of-day data where weather effects vanish beyond grand means. Alternatively, grouping portions of the day results in simpler data, but loses information on hour-to-hour variation. In the present approach, the data is considered as a continuous signal in additive noise, thereby avoiding discontinuities and precisely reflecting weather and other effects. The method of hierarchical regression, used in econometrics and social science research, is utilized (Hausman and MacFadden, 1979). This results in a two-level approach, consisting of the following:

- Level A, where load data for an *individual* household is compressed into a much smaller number of parameters which contain much of the information relevant to the problem at hand, i.e. most of the dependence on household characteristics.
- Level B, where the compressed data extracted from the load shapes of each household in Level A is regressed on the household characteristics in a *cross-sectional* population study.

87 WM 241-3 A paper recommended and approved by the IEEE Power System Engineering Committee of the IEEE Power Engineering Society for presentation at the IEEE/PES 1987 Winter Meeting, New Orleans, Louisiana, February 1 - 6, 1987. Manuscript submitted September 2, 1986; made available for printing December 4, 1986.

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The method used at Level A for data compression consists of defining a set of meaningful predictors and regressing the load shape onto them; clearly, the difficulty lies in *choosing* these predictors, and that is the main topic of this paper.

Once a set of predictors is chosen, load shapes may be compressed into a small set of numbers ("Level A parameters") – specifically, those that parametrize the predictors, and the coefficients that multiply them. Conversely, and more interestingly, given a set of Level A parameters, one can reconstruct the load shape with minimal loss of information. Since the Level A parameters are for various reasons easier to model efficiently as functions of household characteristics, this yields a powerful approach for estimating load shapes given socio-economic, demographic, and appliance holding information.

III. MODELING INDIVIDUAL HOUSEHOLDS

Household-level total home load datasets are large. A three-year study of several hundred homes might contain 10^6 to 10^7 readings. At the same time, the load shapes are often strongly periodic, reflecting diurnal weather variations, weekday-weekend work patterns, and the daily and weekly habits of the occupants. Random irregularities in household periodic behavior can be treated as noise, while systematic irregularities due to holidays or changes in household characteristics must be detected and removed (see Usoro, Schick and Ruane, 1986b). The remaining systematic patterns can essentially be subdivided into weather-independent (lifestyle) and weather-dependent components of the load: the individual household is modeled as

$$y(n) = y_w(n) + y_l(n)$$

where $y(n)$ is the total (household-level) load during hour n, y_w is the weather-dependent component, and y_l is the weather-independent (lifestyle) component. Appliances whose use depends primarily upon the weather, such as electric space heaters and air conditioners, are responsible for the former; essentially lifestyle-based appliances such as electric ranges, clothes washers and dryers, and lighting, comprise the latter.

This approach yields a high rate of data compression, which not only allows more efficient representation of the load shapes but also highlights those aspects of the data which are most likely to be related to the household characteristics – i.e. comprises a more "meaningful" parameter set. Thus, while the load at any given point in time may not be explained efficiently, say, by family income, dishwasher ownership, or commitment to energy conservation for a particular household, the periodic behavior, or the response time to outside temperature changes for that household, are likely to bear a much more direct connection to the household characteristics. Consequently, rather than regressing the load directly onto the household characteristics, the intermediate step in Level A is introduced. A system identification approach is adopted for modeling individual household loads: a model structure is postulated and available data are used to estimate statistically the values of its parameters. Since the final goal is to determine functional relationships between household characteristics and load shapes, the chosen model structure is fundamentally physically-based.

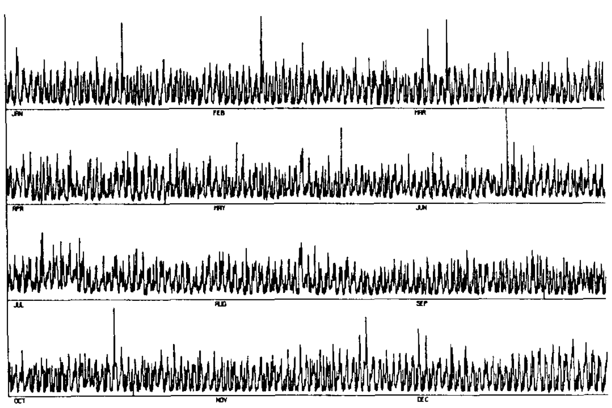

Figure 3.1 (a) Raw data of load exhibiting strong daily and weak weekly periodicities.

A. Weather-Independent Modeling

The goal of this effort was to select functions of time $\phi_i(n)$ to efficiently (parsimoniously) represent the weather-independent component of the load, i.e. to set

$$y_l(n) = \sum_i \alpha_i \phi_i(n)$$

where α_i are household-dependent coefficients to be determined.

The use of Fourier or other orthonormal functions to model the weather-independent component of the load is warranted both by intuition and by analysis of the frequency content of the data. A large number of household-level load shapes were Fourier transformed, and their amplitude spectra were examined. The load shapes yielded line spectra superimposed upon relatively low level noise. For instance, the load shape in Figure 3.1 has a clearly visible daily periodicity, which appears as a series of peaks in the amplitude spectrum at locations corresponding to frequencies of 24 hours and its harmonics. A much weaker periodicity is evident at harmonics of 168 hours (1 week). In contrast, Figure 3.2 appears to be the load shape of a weekend home: weekday loads consist of low level cycling of refrigerators and the like, while weekends show evidence of higher power consumption as well as more erratic consumption patterns. The amplitude spectrum features prominent peaks at the reciprocal of 168 hours and its harmonics, and much weaker peaks related to 24 hour periodicities.

These results were typical of the spectra observed for household-level load shapes, and suggested the use of sinusoidal predictors to express the weather-independent component of the load. Since the goal was to capture the most information in as few terms as possible, some related predictors were also incorporated. The following functions were used:

- *Additive sinusoids:* functions of the form

$$\phi_i(n) = \begin{cases} \sin(\omega n) \\ \cos(\omega n) \end{cases}$$

  The frequencies were chosen to be daily, weekly, and possibly seasonal harmonics.

- *Multiplicative sinusoids:* functions of the form

$$\phi_i(n) = \begin{cases} \sin(\omega_1 n)\sin(\omega_2 n) \\ \sin(\omega_1 n)\cos(\omega_2 n) \\ \cos(\omega_1 n)\sin(\omega_2 n) \\ \cos(\omega_1 n)\cos(\omega_2 n) \end{cases}$$

  The frequency pairs (ω_1, ω_2) were (daily, weekly) and (daily, seasonal) harmonics. These captured a great deal of the seasonal variation in lifestyle patterns. This multiplicative model *approximates* a two-dimensional Fourier transform, first for each day, and then across the days for the entire year.

- *Multiplicative boxcars (dummy variables):* functions of the form

$$\phi_i(n) = \begin{cases} \delta(n)\sin(\omega n) \\ \delta(n)\cos(\omega n) \end{cases}$$

  where $\delta(n)$ is either zero or one, depending on the day of the week to which the data point corresponds. Boxcar functions can capture abrupt

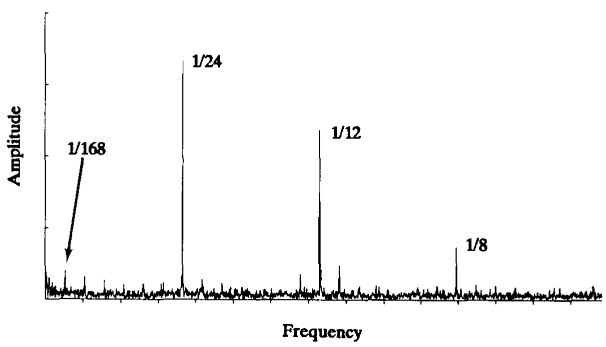

Figure 3.1 (b) Amplitude spectrum of load exhibiting strong daily and weak weekly periodicities.

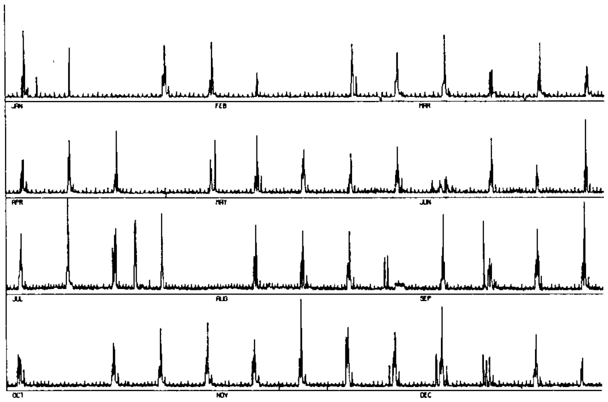

Figure 3.2 (a) Raw data of load exhibiting strong weekly periodicity.

changes, such as the weekday-weekend pattern in Figure 3.2, in a few terms.

- *Additive boxcars (dummy variables):* functions of the form

$$\phi_i(n) = \delta(n)$$

where $\delta(n)$ is either zero or one depending on the nature of the data point. At the limit, this form could take 24 functions corresponding to each hour, and replicate the classical aggregation of hourly data across days.

The model also included an intercept term. Of the above functions, the most useful were the first two; 6 daily and 2 weekly harmonics were sufficient for additive sinusoids, while (3,2) and (2,2) harmonics were used for the (daily, weekly) and (daily, seasonal), respectively. Seasonal harmonics were not used, since seasonal variation was effectively captured by the weather-dependent component.

B. Weather-Dependent Modeling

Weather-dependent load behavior was also expressed as a weighted sum of predictor functions, i.e.

$$y_w(n) = \sum_j \beta_j \, \theta_j(n)$$

where β_j are household-dependent coefficients to be determined. However, the choice of the predictors θ_j was complicated by the fact that different dwellings may have widely varying responses to changes in weather conditions – due, for instance, to differences in exposure and insulation.

Two methods of choosing the weather-dependent predictors were considered. The first involves a detailed thermodynamic household model with non-linear thermostatic control and saturation characteristics. While this model is intuitively justifiable and derives from basic principles, it also causes certain difficulties in practice when model parameters must be estimated for hundreds of households. The second method, approximating the first, is easier to implement and yields satisfactory results.

In this approach, a dwelling is represented as a space enclosed in a shell that protects it from direct contact with the environment. Desirable ambient conditions are maintained within the dwelling by suitable space conditioning devices such as space heaters or air conditioners. The shell has thermal inertia and heat transfer characteristics. The energy consumption of the space conditioning device is proportional to the rate of heat transfer through the shell, provided that this rate remains between a comfort setpoint and a saturation level. Although different sections of the shell ("cells") have different thermal characteristics, experience has shown that an aggregate model lumping the shell into a single effective thermal capacitance yields satisfactory results.

Since ambient conditions within the dwelling are kept constant, the heat transfer effected by the space conditioning device is a function of the shell temperature $T_w(.)$, which is in turn driven by outside temperature $T_o(.)$, i.e.

$$\tau \frac{d}{dt} T_w(t) = -T_w(t) + T_o(t)$$

where τ is a time constant depending, among other factors, on exposure,

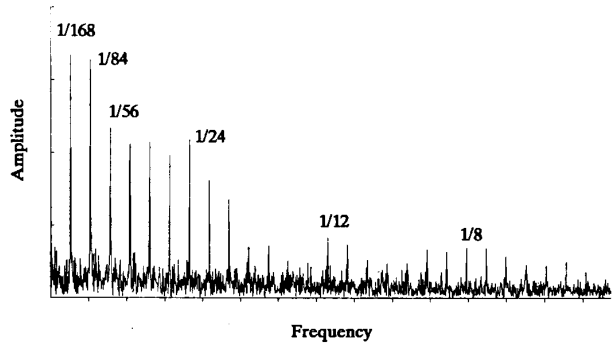

Figure 3.2 (b) Amplitude spectrum of load exhibiting strong weekly periodicity.

size, and insulation. Note that τ is unknown for any given house, and indeed may vary depending on whether the space is heated or cooled; thus, it must be estimated. Assume for the sake of argument that θ_j is a predictor for the weather-dependent component of the load due to cooling. Then, clearly $\theta_j(n) = 0$ if $T_w(n) < T_c$, a comfort setpoint. Likewise, $\theta_j(n)$ is constant (at maximum capacity) if $T_w(n) > T_s$, a saturation temperature. Since T_c and T_s are also household-dependent, they must be estimated for each customer.

Assuming that energy consumption is proportional to T_w when the device is on but not saturated, the dependence of θ_j on the outside temperature T_o is as illustrated in Figures 3.3 and 3.4. The latter shows the different responses of the cooling load to an actual heat wave in Boston for different values of τ. As expected, the system shuts off when the temperature drops below T_c, and saturates when it rises above T_s. Moreover, the figure graphically shows the heat build-up phenomenon: although the peak temperature on successive days may not increase, the peak load in the longer time constant responses continues to increase for some time, due to the accumulation of heat in the house, the ground, etc.

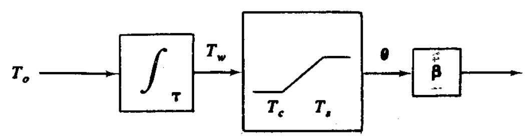

Figure 3.3 Dynamic model for load component due to cooling, illustrating response to outside temperature T_o, household-dependent time constant τ, gain (proportionality constant) β, comfort setpoint T_c, and saturation temperature T_s.

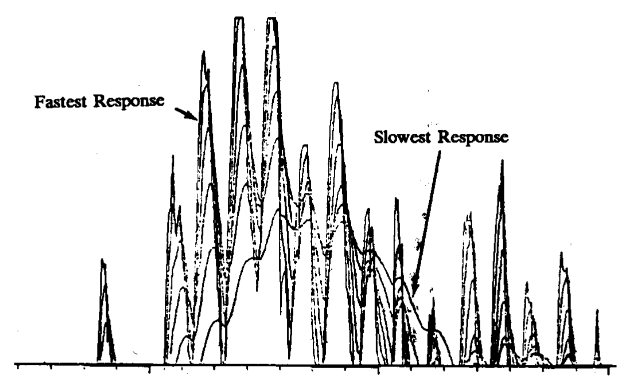

Figure 3.4 Dynamic responses to outside temperature for various values of the time constant τ, during a Boston-area heat wave lasting two weeks. Fastest response corresponds to smallest value of τ.

Similar arguments can be made for the heating load, so that (indexing with j the heating and cooling components) the weather-dependent load component is represented as

$$y_w(n) = \sum_j \beta_j\, \theta_j(\, n\, , T_o(n), \tau_j, T_{cj}, T_{sj}\,)$$

A parametric model has thus been formulated including weather-dependent and weather-independent load components; it is necessary to estimate the values of its parameters for each household.

C. Parameter Estimation

The parameter estimation problem is to fit the whole-house load model

$$y(n) = y_l\,(n) + y_w(n)$$
$$= \sum_i \alpha_i\, \phi_i(n) + \sum_j \beta_j\, \theta_j(\, n\, , T_o(n), \tau_j, T_{cj}, T_{sj}\,),$$

where the dependence of θ_j on its parameters τ_j, T_{cj}, and T_{sj} is nonlinear. Thus, while the coefficients α_i and β_j may be estimated by linear regression, the parameters of θ_j cannot. For any given value of these parameters, however, linear regression may be used to yield estimates of the coefficients. Thus, the following algorithm is used:

- An outer "optimization loop" chooses the $\tau_j^{(k)}$, $T_{cj}^{(k)}$, and $T_{sj}^{(k)}$.
- For each choice, the $\theta_j^{(k)}(.)$ are computed exactly.
- The gains $\alpha_i^{(k)}$ and $\beta_j^{(k)}$ are computed by regression.
- If this choice does not result in a minimal residual sum-of-squares, the procedure is repeated with $k \rightarrow k+1$.

In this algorithm, the predictors are thus not constant, but functions of unknown parameters, which are themselves optimized to yield the best fit. Note that since the number of parameters is fixed, the residual sum-of-squares is a sufficient goodness-of-fit criterion.

Some simplification is possible, with an increase in computation speed – an important factor since each evaluation of the objective function involves solving a linear regression over as many as 8760 points. For example, heating and cooling parameters influence the load at different times, and although such house characteristics as insulation do not change from season to season, lifestyle patterns do change enough to warrant the independent estimation of these parameters. Moreover, it was found in the test data that T_{sj} could be ignored, since temperatures seldom reached values extreme enough to drive the equipment into saturation. Since the number of function evaluations is a nonlinear function of the number of parameters, these actions resulted in significant computational savings.

Weather-dependent load commonly changes qualitatively throughout the day, reflecting the lifestyle of the household members, and resulting in some interaction between behavioral factors and the weather. Rather than estimating separate weather-dependent predictor parameters at different times, which would be computationally expensive, only the gains θ_j were allowed to vary: three periods were used, covering 1-8, 9-17, and 18-24 hours.

Finally, the results of the parameter estimation process are tested to check whether or not a weather-dependent component truly exists: simple hypothesis tests are performed at the beginning and the end of the process – for both cooling and heating load components. At the beginning, the estimated gains are analyzed given the initial guesses for time constant and temperature setpoints; if the gains are statistically insignificant or nonphysical (e.g. negative) for all periods of the day, it is concluded that the weather component in question does not exist. Similarly, gains as well as time constants and temperature setpoint estimates are tested at the end of the estimation process: once again, statistically insignificant gains or nonphysical values for the estimated time constants, temperature setpoints, or gains, suggest that the corresponding weather components are not present.

IV. RESULTS

The technique discussed here has been applied to residential whole-house data from three service areas. Some typical examples, involving customers of the Boston Edison Company, are discussed in this section.

Figure 4.1 shows a very regular pattern throughout the year, with little deviation from a regular daily periodicity. Tests suggest that no weather-dependent load component is present, which is confirmed by the survey data. Note that the missing data in early September do not prevent the process from providing a reasonable reconstruction. This segment, as well as one in late May and early June, were flagged by the Utility as invalid data and were therefore ignored in the parameter estimation process. The seasonal variation in the peaks of the daily curves is captured well. Finally, observe that reconstruction is poor on Christmas Eve, where the load deviates significantly from the usual pattern. Such holiday effects can be anticipated.

An example of strong weekly periodicity appears in Figure 4.2 (a). The atypical "quiet periods" are automatically detected and excluded during parameter estimation. The weekly variation is especially clear in Figure 4.2 (b), where daily averages for weekdays and weekends are given for selected months; note that the reconstruction captures this variation extremely well. Once again, no weather-dependent load component is present.

The survey indicates that the customer in Figure 4.3 (a) has electric space heating as well as a room air conditioner, and the parameter estimation algorithm detects the presence of both components – as can be seen in Figure 4.3 (b), where the weather-dependent and weather-independent components are each plotted. The end of February is noteworthy: a warm spell occurred, and the customer appears to have turned off the heater, resulting in a slight overestimation of the weather-dependent load. There was a heat wave in July, as is clear in the increased load during that period; the air conditioner was apparently turned off late at night, and that effect is captured well by the three-way split of the gains, as discussed earlier.

Although the analysis was directed to individual residential customers, the resulting algorithm can also be applied, for instance, to total system load – including commercial and industrial loads. This approach may be used to disaggregate weather-dependent and weather-independent components of the load, as can be seen in Figure 4.4. The reconstruction for the entire year is excellent, with the exception of some holidays; no special effort was made to reflect holiday behavior.

For a data set of 125 households, the coefficient of determination (R^2) ranged from a low of 18.6 to a high of 86.8. As might be expected, the poorest performance was for irregular loads lacking weather-dependent components. More systematic loads, i.e. those with significant periodicities and weather dependence, performed best.

CONCLUSION

A two-tiered procedure has been formulated for modeling and analyzing residential end-use load shapes. At the first level, the whole-house data is modeled as the sum of a weather-independent (lifestyle) component, and a weather-dependent component. The former is expressed as a weighted sum of orthogonal functions (sinusoids, boxcars, and their products), and the latter as a weighted dynamic response to outside temperature, parametrized by certain household-dependent quantities (time constant, comfort setpoint, saturation temperature).

The algorithm has been applied to several data sets, and results indicate good fit with low-order models: hourly data for a year (8760 observations) are compressed into approximately sixty parameters, and successfully disaggregated into weather-dependent and weather-independent components. Moreover, the parameter set extracted from the data correlates well with household characteristics (second level), providing an effective method for end-use load shape estimation from whole-house metered data.

ACKNOWLEDGMENTS

This effort was funded by the Electric Power Research Institute under contract RP 2145-1. The guidance and support provided by Dr. Steven D. Braithwait, EPRI Project Manager, is gratefully acknowledged. Thanks are also due to the industry advisors – particularly Dr. Susan Piotroski and Roger Boudreau of the Boston Edison Company, who kindly supplied the data on which the present results are based.

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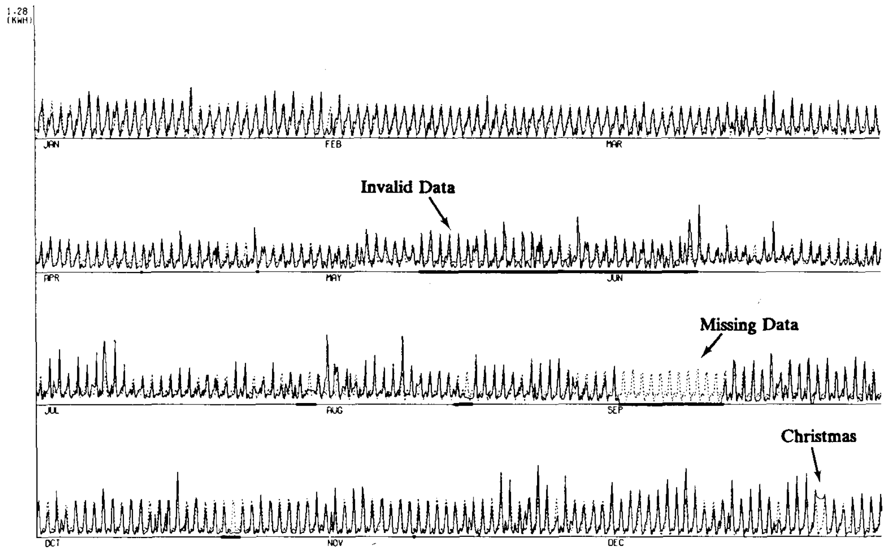

Figure 4.1 Data (solid) and reconstruction (dotted) for household exhibiting regular daily pattern.

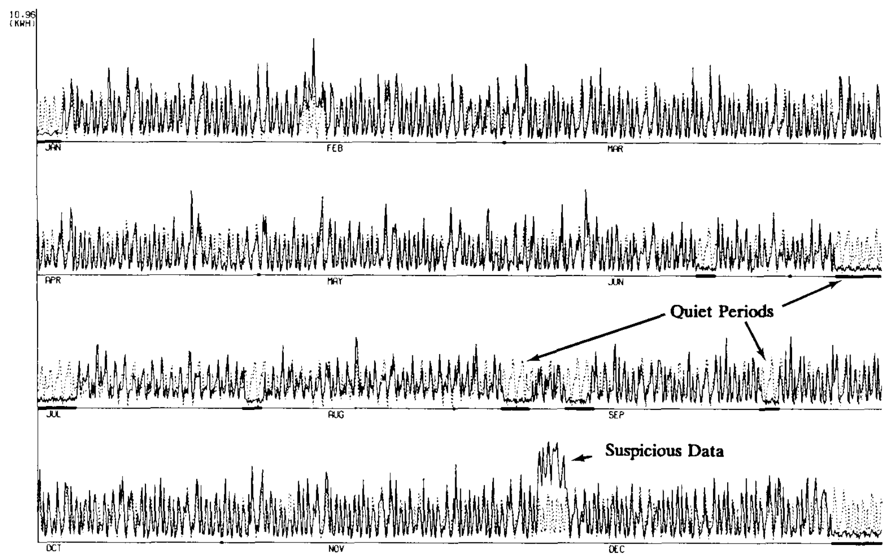

Figure 4.2 (a) Data (solid) and reconstruction (dotted) for household exhibiting daily and weekly periodicities.

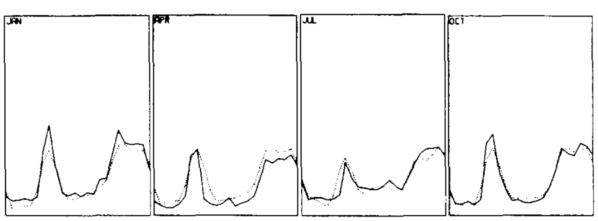

Figure 4.2 (b) Weekday averages of data (solid) and reconstruction (dotted) for household exhibiting daily and weekly periodicities, selected months.

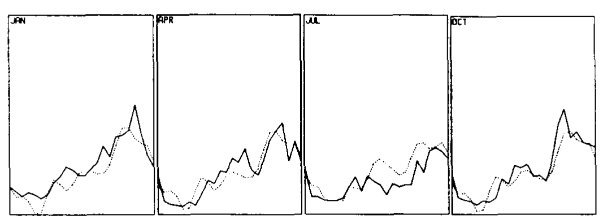

Figure 4.2 (c) Weekend averages of data (solid) and reconstruction (dotted) for household exhibiting daily and weekly periodicities, selected months.

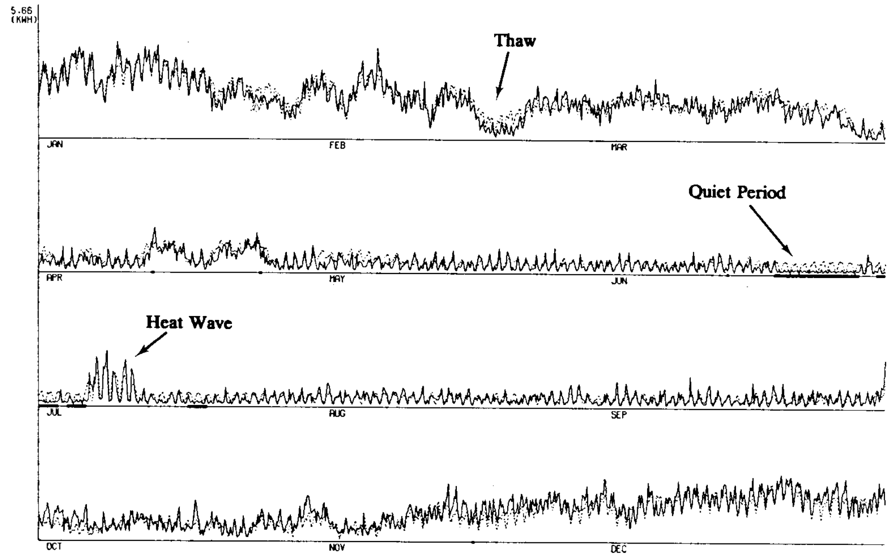

Figure 4.3 (a) Data (solid) and reconstruction (dotted) for household with electric space heating and room air conditioner.

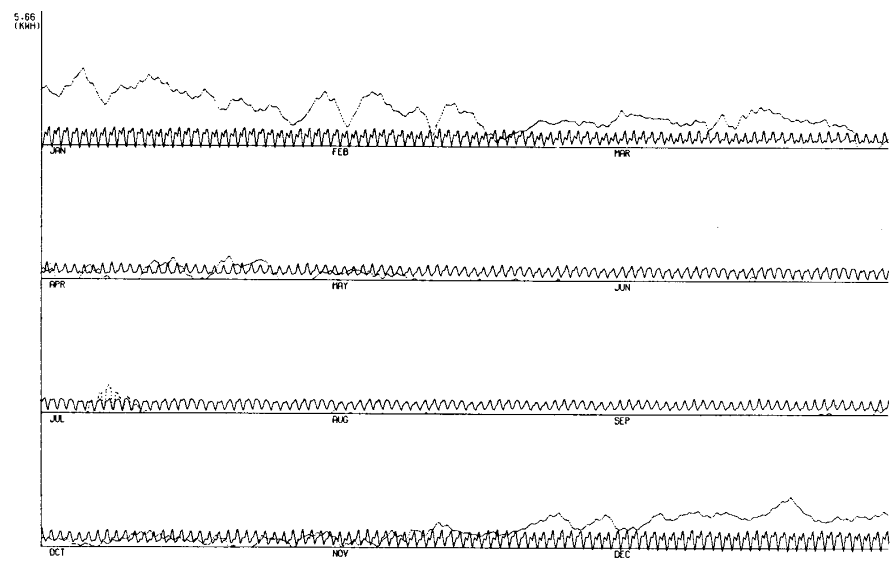

Figure 4.3 (b) Reconstruction of weather-dependent (dotted) and weather-independent (solid) components for household with electric space heating and room air conditioner.

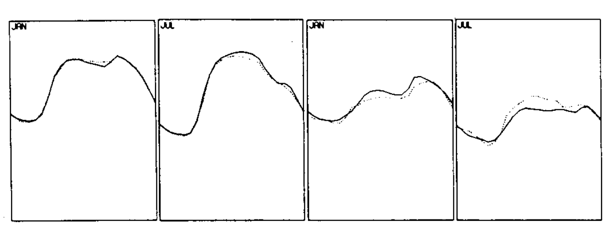

Figure 4.4 (b) Weekday (left) and weekend (right) averages for data (solid) and reconstruction (dotted) of Boston Edison total system load, selected months.

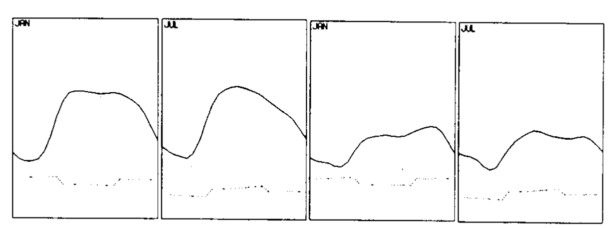

Figure 4.4 (c) Weekday (left) and weekend (right) averages for weather-dependent (dotted) and weather-independent (solid) components of Boston Edison total system load, selected months.

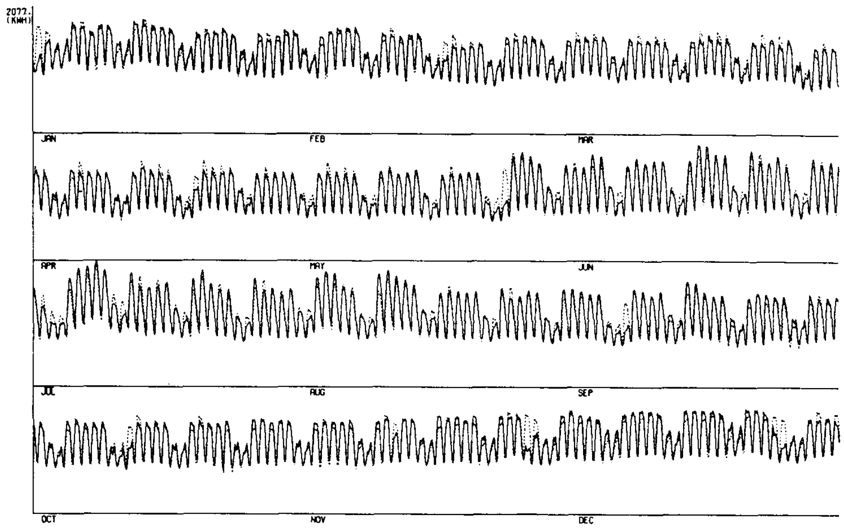

Figure 4.4 (a) Data (solid) and reconstruction (dotted) of Boston Edison total system load.

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