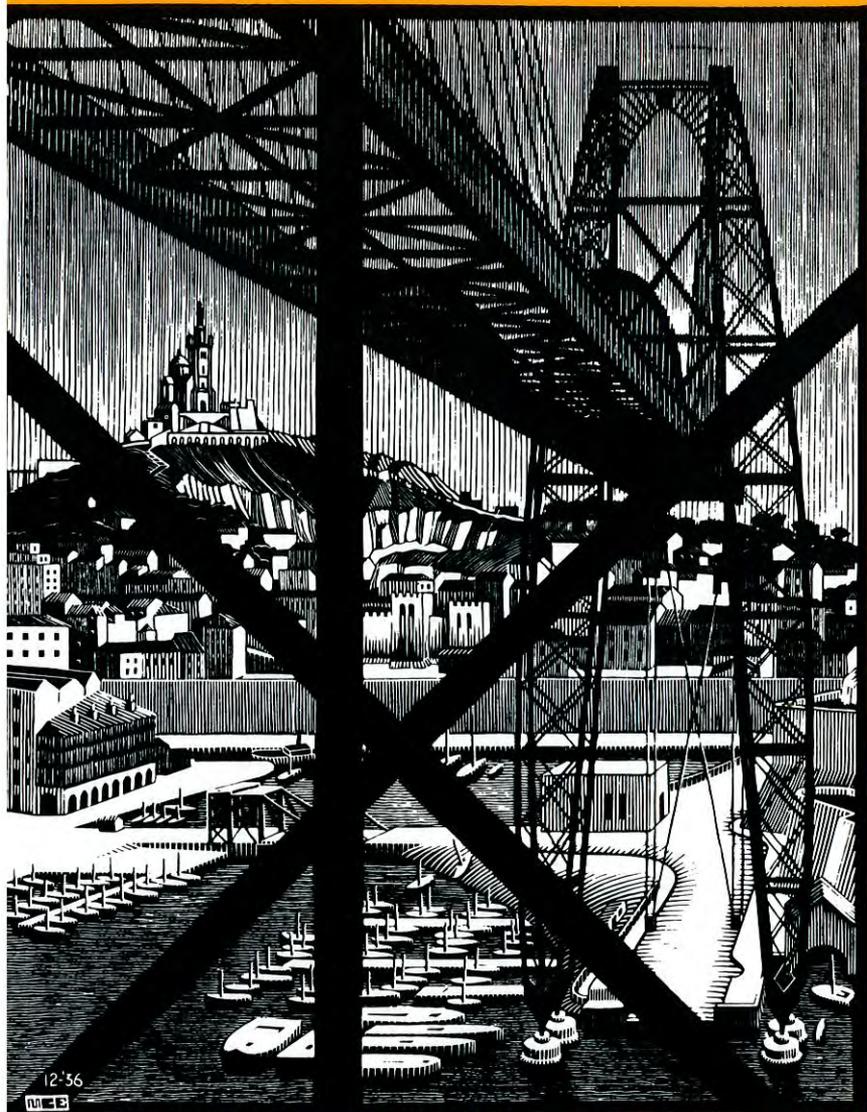


State of the Art of Energy Efficiency *Future Directions*



Edited by EDWARD VINE
and DRURY CRAWLEY

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STATE OF THE ART
OF ENERGY EFFICIENCY:

Future Directions

American Council for an Energy-Efficient Economy
Series on Energy Conservation and Energy Policy

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State of the Art of Energy Efficiency:
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American Council for an Energy-Efficient Economy
Washington, D.C., and Berkeley, California

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Universitywide Energy Research Group
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State of the Art of Energy Efficiency: Future Directions

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Published by the American Council for an Energy-Efficient Economy
1001 Connecticut Avenue, N.W., Suite 535, Washington, D.C. 20036.

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Cover design by Wilsted & Taylor

Book design by Paula Morrison

Book typeset by Campaigne & Associates Typography

Printed in the United States of America by Edwards Brothers Incorporated

Library of Congress Cataloging-in-Publication Data

State of the art of energy-efficiency: future directions / edited by Edward Vine and Drury Crawley.

304 p. 23 cm. — (Series on energy conservation and energy policy)

Includes bibliographical references and index.

ISBN 0-918249-11-2: \$24.50

1. Buildings—Energy conservation I. Vine, Edward L. II. Crawley, Drury, 1957— . III. American Council for an Energy-Efficient Economy.
- IV. University of California (System). Universitywide Energy Research Group.
- V. Series.

TJ163.5.B84S726 1991

696—dc20

91-12339

CIP

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End-Use Load Shape Data Application, Estimation, and Collection

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As electric utilities increasingly adopt least-cost integrated resource planning processes, their information needs about demand-side management (DSM) options expand considerably. Many DSM alternatives offer the potential to meet a significant share of consumers' demands for energy services by means of increased energy efficiency (Krause and Eto 1988). However, comprehensive information on the cost and performance of these alternatives has been slow to develop. Current utility supply-side planning methods involve detailed assessments of alternative resource plans that take explicit account of the time-varying nature of customers' demands for electricity. In order for demand-side options to be treated comparably to generation resources, planners need reliable information on the impact of these options on system loads.

Yet information on the end-use components of aggregate electricity loads and how these components can be modified is not widely available, especially information for the time intervals used to evaluate generation options. A recent assessment of least-cost planning (LCP) concludes that uncertainty about the performance of DSM activities, including their impact on load shapes, is a major barrier to increased utility reliance on DSM for meeting customers' demands for electricity services (Goldman, Hirst, and Krause 1989).

The goal of this chapter is to assess progress in reducing this uncertainty. The chapter reviews leading efforts to collect, estimate, and apply end-use load shape data for utility planning purposes.

This chapter addresses utilities' need for load shape data from residential and commercial buildings (although other groups, such as the building energy research community, also need these data). We do not review industrial-sector end-use load shape data because efforts to develop these data—which are as important as residential and commercial end-use load shape data—are still in their infancy.

The first section of the chapter reviews utility applications of end-use load shape data; the next two sections review current efforts to obtain end-use load shape data by estimation and by direct metering. Our discussion of these three topics begins with a brief historical summary and a review of the state of the art. We also speculate on promising future areas of research. These speculations form the basis for a final section, which describes our vision of the next generation of end-use load shape data applications, estimation, and collection.

Utility Applications of End-Use Load Shape Data

End-use load shape data play a crucial role in several aspects of utility planning, including demand-side technology or program performance, load forecasting, and supply- and demand-side resource integration. The increased importance of these planning functions is the principal reason for current utility interest in acquiring end-use load shape data.

At the same time, these applications require different types of end-use load shape data. To forecast system load shapes for capacity planning, average load shapes by customer or rate class may be sufficient; needed information may include seasonal or weekly fluctuations and the hourly pattern of load shapes over a 24-hour period. For assessing a list of potential DSM options or developing a comprehensive integrated resource plan, planners may need additional load shapes for major end uses and even for specific technologies within those end uses. The precision required of this information will also depend on whether the analysis is a preliminary one or the final review prior to resource acquisition. Finally, a comprehensive analysis of the measured performance of a demand-side technology or program will require substantial data in addition to those on load shape in order to assign causal linkages between demand-side intervention and its measured consequences.

In this section, we review these three types of applications in order to better understand the motivation for efforts to estimate and collect end-use load shape data, efforts described in the following sections.

Demand-Side Management Applications of End-Use Load Shape Data

Some of the earliest applications of end-use load shape data can be found in early evaluations of DSM programs designed to modify utility load shapes. Examples include old reports by the Association of Edison Illuminating Companies' (AEIC) Load Research Committee examining the load shape impacts of marketing specific end uses, such as electric water-heating and air-conditioning (AEIC 1974). Applications also appear in research sponsored by the U.S. Department of Energy (DOE) and Electric Power Research Institute (EPRI) on the impacts of time-of-day electricity tariffs on various customer classes (Caves, Christensen, and Herriges 1984) and in DOE and EPRI evaluations of the aggregate impacts of utility direct load control programs.

More recently, it has become evident that planners must be aware of the impacts on load shape of all demand-side technologies and programs, not just those that address utility peak demands. For example, the Hood River Conservation Project, a landmark demonstration of the blitz approach for deploying residential DSM, aimed primarily at saving energy but also had measurable load shape impacts. The project involved the wholesale retrofitting of an entire community in Oregon. The retrofits stressed improvements to the thermal integrity of the homes. As part of the project, the electrical demands of 320 homes were separately monitored. The monitoring permitted researchers to quantify peak demand savings of more than 0.5 kW/household overall and more than 0.8 kW/household for electrically heated homes (Stovall 1989). More importantly, these peak demand savings, when combined with overall energy savings, indicated that household load factors had declined (a load factor is defined as the average demand divided by the peak demand). This observation led to the suggestions that further improvements could be made by downsizing home heating equipment in response to the reduced thermal loads.

Similarly, evaluation, as well as monitoring of demand-side technologies or programs, has been substantially refined by the availability of end-use data. For example, in evaluating the net impact of utility direct load control (DLC) programs, it is well known that the normal cycling behavior of controlled appliances

may or may not be affected by a utility's program: that is, absent the program, significant cycling may already be the pattern of normal operation. Thus, the DLC program's impact on aggregate load shape is a function of how much the program has modified the distribution of appliance cycling times for a population of users. Evaluating these distributions requires large samples and data collection on days when the program is operating and on days when it is not. See Braithwait 1989 for a recent evaluation of a DLC program that takes explicit account of these distributions.

We expect that applications of end-use load shape data for DSM evaluation will assume increased importance as demand-side planning becomes more integrated into utility planning processes. In particular, the use of competitive resource acquisition mechanisms (such as demand-side bidding) to solicit demand-side resources from third parties will increase the need for explicit measurement of demand-side program savings. End-use load shape data should play a prominent role in these evaluations.

Forecasting Applications of End-Use Load Shape Data

Forecasting utility system load shapes through the summation of end-use load shapes is the logical consequence of utility adoption of the end-use framework for forecasting annual energy use. One of the earliest examples of this linkage is the system of forecasting models developed by the California Energy Commission (CEC). In response to a statutory charge to prepare forecasts of future energy use that explicitly capture the effects of California's building and appliance standards, CEC developed the first generation of end-use forecasting models for application to distinct utility service territories. The modeling system, which continues to be refined by the CEC, included an end-use peak demand model to forecast hourly system loads for separate end uses during a utility peak day (Jaske 1980). The model operates as a post-processor to forecasts of annual end-use electricity demands predicted by a separate model. The explicit linkage between the annual energy demand forecast and the system peak-day load shape ensures an important consistency between the forecasts for annual energy and peak demand that is often lacking when the two quantities are forecast separately.

The commercially available counterpart to the CEC's peak demand model is the Hourly Electric Load Model (HELM). HELM is a flexible load shape forecasting model that takes user-entered forecasts of annual energy sales at a user-selected level of disaggregation (for example, total system, customer class, end use) and monthly, daily, and hourly allocation factors, again at optional levels

of detail (typical days, 8,760 hours), and produces a system load shape forecast (ICF 1985). Most utilities currently use HELM at the customer class level, although some utilities model weather-sensitive uses separately. Indeed, much utility interest in end-use load shape data is for monthly and annual aggregations of these data for energy forecasting or other purposes unrelated to load shape.

For the future, we expect forecasting applications for end-use load shape data to increase. For example, some analysts believe it may soon be possible to produce annual energy forecasts by aggregating hourly end-use load shape forecasts (Eto, Blumstein, and Jaske 1988). Forecasting energy use on an annual basis is largely a matter of convenience. Many important energy use decisions (such as the usage, as opposed to the purchase, of an energy-using durable good) take place at a much finer level of temporal disaggregation. These forecasting efforts will only proceed, however, after significant advances in our understanding of the causal factors influencing energy use over shorter time intervals.

Integrated Resource Planning Applications of End-Use Load Shape Data

A distinguishing feature of early applications of load shape data is that they were not fully integrated into the process of utility resource planning. Despite producing forecasts of hourly system loads for the peak day, for example, the CEC model passed a forecast of only total annual energy and peak demand to the resource integration planners. Similarly, for most evaluations of demand-side resources, the load shape impacts of specific demand-side resources are manually subtracted from aggregate system load shapes, a practice that may ignore interactive effects among end uses and other DSM programs.

An emerging application of end-use load shape data is better integration of demand-side resources into the utility planning process. From a purely mechanical standpoint, these improvements are exemplified by the recent availability of demand-side screening and integrated resource planning models, which facilitate the analysis of demand-side resources. From a more theoretical standpoint, end-use load shape data are beginning to play an extremely important role in extending demand-side planning into the realms of transmission and distribution (T&D) system planning and fuel-switching.

Demand-Side Screening Analysis

Detailed analysis of all available demand-side resources is inefficient

because initially only a handful of demand-side options will be appropriate for serious consideration. Reducing the long list of available resources is called screening analysis. At this initial stage of the planning process, shortcuts are taken to facilitate rapid analysis of a large number of options. For example, rates of implementation and marginal costs of programs may be fixed regardless of the size of the demand-side intervention. At the same time, due to their importance for utility planning, the load shape characteristics of demand-side resources and time-differentiated marginal costs of electricity generation will often be retained for this stage of analysis. Models that support screening analyses using end-use load shape data include COMPASS (SRC 1989) and DSManager (EPS 1989).

Integrated Resource Planning Models

With a manageable list of demand-side resources identified for further analysis, the need to consider these resources on an equal footing with those on the supply side has led to a whole new class of planning models. These models, called integrated resource planning models, combine historically distinct modeling capabilities, such as load forecasting and production costing, into a single piece of software. While extensive calibration and coordination of data transfer with the more detailed stand-alone models for each modeling task are required, the ability of these new models to carry out an integrated analysis rapidly makes them extremely attractive for strategic planning. Well-known integrated planning models that feature end-use load shape data handling capabilities include UPLAN (Lotus Consulting Group 1986), MIDAS (Farber, Brusger, and Gerber 1988), and LMSTM (Decision Focus 1982). (See also Eto 1990 for an overview of issues associated with the use of demand-side screening and integrated resource planning models.)

Published examples of the application of end-use load shape data with an integrated resource planning model are rare, although many such studies exist as proprietary consultant reports or as parts of utility regulatory filings. A recent exception is Comnes et al. 1988, which used the LMSTM model to evaluate the cost-effectiveness of utility incentives to stimulate adoption of cooling thermal energy storage technologies for buildings.

T&D System Planning

Most integrated resource planning efforts by utilities consider demand-side options only as means to modify decisions on whether and how to expand generating capacity. The availability of end-use load shape data and geographically differentiated utility substation

metering has led to the possibility of also deploying demand-side programs to avoid T&D investments. A recent study examined utility T&D planning and concluded that significant savings could be realized by targeting DSM to specific geographic locales where the avoided cost of T&D was high due to the imminent need to upgrade the capacity of substation distribution transformers (Rosenblum and Eto 1986).

Fuel-Switching

Similarly, an integrated resource planning process should also (but typically does not) consider fuel-switching as a means for meeting customer's demands for energy services. End-use load shape profiles of both electric and gas energy-using equipment can play important roles in these evaluations. At this time, we are aware of only one study that has begun to compare these profiles, focusing on residential appliances (Quantum Consulting 1989).

The Need for End-Use Load Shape Data

It is probably safe to say that the sophistication of utility applications for end-use load shape data (in particular, currently available software models) exceeds the quality and quantity of currently available data. We see no sign that this trend will end soon. Acquiring end-use load shape data, however, is an expensive undertaking with large differences in cost between end-use load metering and load shape data estimation. Therefore, the relevant economic question to which we now turn is, given the value of end-use load shape data for utility planning, what is the most cost-effective means for obtaining them?

Estimating End-Use Load Shapes

Prior to the recent wave of end-use metering projects, the only means for obtaining load shape data unique to local conditions was estimation. Estimation methods have historically relied on extensive and largely unverifiable engineering judgment. Indeed, concern over the reliability of these judgments has been a major impetus for the end-use metering efforts described later. However, increased collection of supplementary data, such as customer mail surveys and load research data, has led to a whole new generation of estimation methods. Moreover, the availability of end-use metered data provides, for the first time, the potential for validating the estimation methods. When validated, these methods offer the promise of producing end-use load shape data at a fraction of the cost of metering.

Historical Development of Estimation Methods

Traditional approaches to load shape estimation typically have used engineering simulations. The basic approach was to use available supplementary data, such as results of mail surveys, on a subset of the building population (single family dwellings, large offices, and so on). Engineering judgment was applied to these data to create a prototypical building whose energy-use patterns were considered representative of the subset of buildings being studied. An hourly building energy simulation program then produced the end-use load shapes.

The basic issue for this method, as for all estimation methods, is calibration. For the earliest efforts, calibration was only possible at an extremely high level of end-use and temporal aggregation (usually monthly total energy bills). Even then, because lighting and equipment loads were used only as inputs to the thermal simulations, calibrations typically estimated only the relative magnitudes, not the shapes, of these loads. In the absence of more detailed data, independent judgment as to the accuracy of simulated hourly load shapes has been largely a matter of faith. Indeed, many early load shapes developed by the above method exhibit the characteristic square shape that arises from the simulation of prototypes. (See, for example, Akbari et al. 1990 for a review of some of these studies.)

State-of-the-Art Estimation Methods

The passage of the Public Utilities Regulatory Policy Act of 1978 (PURPA) provided an unanticipated benefit for end-use load shape estimation. PURPA directed utilities to carry out detailed cost-of-service studies, based on hourly measurement of customer loads, for the purpose of reforming rate design. As a result, hourly whole-building load shape data have become widely available. The benefit for end-use load shape estimation lies in the fact that these data provide a control for reconciling estimates of hourly or even shorter-interval load shapes. Unfortunately, until recently little or no information on customer characteristics was collected along with the load research data. A number of utilities, seeing the value of load research data for other than cost-of-service applications, have begun to collect characteristics data and in some cases to expand the samples to represent market segments in addition to rate classes.

Researchers have used at least six distinct methods of estimating end-use load shape in order to utilize these data. The methods are (1) one-dimension application of the Stephan-Deming Algorithm, (2) the variance allocation approach, (3) the End-Use Disaggregation Algorithm, (4) the conditional demand approach,

(5) the bi-level regression approach, and (6) the Statistically Adjusted Engineering (SAE) approach. For purposes of exposition, it is useful to separate the methods that are primarily deterministic from those that are primarily statistical (although, as we shall see, this distinction breaks down for several of the methods).

The deterministic methods, which include methods 1 through 3, rely on exact reconciliation to an hourly control total, which is provided by the whole-building load research data. Of the three methods of which we are aware, reconciliation starts with an engineering simulation of the sort relied upon by the earliest load shape estimation methods. The later methods, however, typically rely on much more detailed information to develop the simulation input (thereby minimizing the extensive reliance on engineering judgment that characterized many early efforts). More importantly, they start with the assumption that an engineering simulation will not equal the measured, whole-building load shape. Each method differs in the manner by which the difference between the observed total and the sum of the initial, simulated estimates is allocated to constituent end uses.

The most straightforward allocation method, called the one-dimensional application of the Stephan-Deming Algorithm, is simple proration of the difference between the observed total and the sum of the simulated end uses based on the relative magnitudes of end uses in the original simulated estimates (SRC 1988). If, for example, there are only two end uses and one is simulated to be twice the size of the other, two-thirds of the difference between the simulated total and the control total is allocated to the larger end use. This approach has been used to estimate commercial sector end-use load shapes for the Southern California Edison Company. More flexible versions of this simple allocation have been implemented in the RELOAD software discussed in the next section.

Another allocation rule, called the variance allocation approach, involves prorating the difference between the simulated and control totals based on the observed statistical variation in the simulated end-use loads (Schon and Rodgers 1990). The rationale for this approach is that highly variable loads are more likely than relatively stable loads to diverge from simulation-based estimates of their magnitudes. (Of course, the magnitude of the observed variation is also related to the magnitude of the initial load.) This approach has been applied to a study of commercial buildings in the Florida Power and Light Company service territory.

A final deterministic reconciliation method, called the End-Use Disaggregation Algorithm, treats weather-sensitive end uses

(cooling and heating) separately from other end uses (Akbari et al. 1988). An exact estimate of the weather-sensitive end use is first derived from a regression of the control totals provided by the whole-building load research data on temperature for each hour of the day. (An intercept for the weather-sensitive end use estimated from an analysis of the simulated end-use data is also included to account for non-weather-sensitive cooling or heating.) The allocation of any remaining differences between the simulated and control total takes place only after the weather-sensitive end use has been subtracted from the control total. The allocation is based on the magnitude of the initial simulated loads (as is done in the Stephan-Deming method), subject to continuity constraints placed on adjacent hours to reduce fluctuations from hour to hour. The motivation for this approach is the assumption that the correlation of measured whole-building loads to observed weather is superior to simulations for estimating weather-sensitive end-use load shapes. The approach has been used to develop end-use energy utilization intensities (EUIs) and load shapes for commercial buildings in the Southern California Edison service territory (Akbari et al. 1989).

Statistical methods, which include methods 4 through 6, represent another major approach for utilizing whole-building load shape data in developing load shapes. As with the deterministic methods, the principal aim is to reconcile selected explanatory variables with some control total. For the deterministic methods, the explanatory variables are taken from an engineering simulation so as to provide a physical basis for the reconciliation (that is, we are adjusting estimates of end-use loads to match an observed or estimated control total), and the reconciliation to the control total is exact. The statistical methods typically rely on regression techniques that correlate explanatory variables with the hourly control total. These variables need not all be physical, and the reconciliation to the control total is an approximate one usually expressed as a goodness of fit.

The earliest application of the statistical method to end-use load shape estimation—called the conditional demand approach—was a direct extension of the conditional demand techniques used to estimate annual energy utilization intensities, which express end-use energy use per unit of floor area, or unit energy consumption (UEC), which expresses energy use per appliance. The conditional demand approach is essentially a correlation analysis of the energy use of many separate premises, such as homes or offices, against the portfolio of energy-using equipment in each of these premises. The analysis seeks to determine the difference in observed load due to the presence of a given energy-using device, all other things

being held equal. This difference is taken to be the energy contribution of the device. The technique was first applied to annual and monthly billing data (Parti and Parti 1980). With the availability of whole-building load shape data, the extension of the technique to an hourly time-step was an obvious one. Published applications of this approach include Hill 1982; Parti and Sebald 1984; and Aigner, Sorooshian, and Kerwin 1983.

Purely correlational methods for end-use load shape estimation can be criticized for ignoring (or making little explicit use of) known determinants of energy use (such as the influence of weather on heating and cooling loads). Recently, two very different methods for incorporating this knowledge within a statistical framework have been developed. In effect, these methods are hybrids of the engineering approaches that underlie the deterministic methods and the previously described statistical correlations.

The first method, called the bi-level regression approach, involves two levels of time-series and cross-section regression analyses (1986). In the first level, the hourly load of individual households is regressed both against weather-related variables and against sine and cosine functions, which capture daily, weekly, and seasonal periodicity in loads that are independent of weather. In the second level, the coefficients estimated in the first level (separately for each individual household) are regressed as a group against customer characteristics.

The second method, the SAE approach, is very close in spirit to the deterministic reconciliation methods (CSI/CAI/ADM 1985). First, an engineering simulation is developed to provide an initial estimate of end-use loads. (A more recent implementation of this approach incorporates metered end-use load shape data from a limited sample of premises as the initial estimate for selected end uses. See Caves, Windle, and Kendall 1988.) Next, the initial estimates are regressed against the control totals, which are averages of hourly energy use for typical days. The estimated coefficients can then be thought of as adjustment factors that reconcile the initial estimates to the control total. In other words, correlational analysis is used to perform the allocation of differences statistically, whereas, in the first three methods, the allocation is performed deterministically.

Deterministic and statistical estimation methods both exhibit desirable qualities for end-use load shape development. Deterministic methods rely on engineering simulations that provide a direct physical link between loads and their causes. The specificity of engineering simulations also facilitates subsequent planning analyses of the likely effect of introducing demand-side technologies. The

price of such specificity is the cost of obtaining the detailed information required to develop an engineering simulation. Statistical methods are valuable because, unlike engineering simulations, they do account for behavioral dimensions. Physically identical structures will use energy differently because energy-use decisions are made by individuals, not buildings. To the extent that the explanatory variables are independent, exhibit variation across the sample, and, most importantly, are statistically significant, statistical techniques can capture these behavioral influences implicitly. However, because the physical underpinnings of energy use are suppressed, the resulting models of energy use may not be equally amenable to what-if types of analysis. Of course, from the more limited standpoint of end-use load shape data development, the issue is the accuracy of these methods and their costs relative to alternative methods of obtaining these data.

Validating End-Use Load Shape Data Estimates with Measured Data

The availability of end-use metered data provides, for the first time, the opportunity to validate end-use load shape estimation methods. However, efforts to use these data for this important task remain in their infancy; we are aware of only two studies, both examining only residential end uses, that have used end-use load shape data to validate estimates.

The first study focused not on end-use load shapes, per se, but on the integrated sum of the hourly values to an annual energy use total by end use (Pratt et al. 1990). In this study, metered residential end-use data from several metering projects were compared to estimates of these end uses developed by conditional demand and engineering studies. The conditional demand estimates were found to be in good agreement (a statistical difference of 10% at the level of annual energy use totals) with the metering studies for refrigerators, freezers, dryers, ranges, and central air-conditioning. Poor agreement was found for dishwashers (the conditional demand estimate was too high), hot water (too low), and space heating (too high, although the comparison is suspected to have been influenced by the weather normalization method applied to the various study results). The engineering estimates were found to be in good agreement with the metering studies for water heating, refrigeration, and clothes washing (clothes washing was not examined by the conditional demand studies), but were in poor agreement for space heating (too high), central air-conditioning (too high), ranges (too high), and dishwashers (too high).

A second study evaluated the accuracy of estimated load shapes using the SAE and the bi-level regression approaches described above (CSI/CAI/SSI 1989). The validation was performed using residential end-use metered data gathered by the Pacific Gas and Electric Company and an engineering simulation for each load. For the SAE approach, substantial improvement over the engineering load estimates was observed for the weather-sensitive end uses. For the non-weather-sensitive end uses, the SAE approach appeared to introduce errors to the engineering load estimates. Finally, the SAE weather-sensitive end-use loads were more accurate for average days than for peak days. For the bi-level regression approach, the most accurate loads were estimated for central air-conditioning and clothes drying, while the least accurate loads were those estimated for refrigerators and water heaters.

These validation studies suggest that, at this time, statistical end-use load shape estimation methods may be well suited for capturing scheduled, non-weather-sensitive end uses. More importantly, they substantiate the potential reliability of the estimation methods for obtaining end-use load shape data at costs far less than end-use metering. The lack of validation studies for the deterministic methods precludes conclusions at this time. Additional validation efforts for all the methods over a wider range of locations, building types (especially in the commercial sector), and end uses will be required before the methods can be regarded as complete substitutes for end-use load metering. However, as we shall describe, it is not clear that future load shape data development efforts should be faced with such an either/or decision.

End-Use Load Shape Data Collection

The most intuitively appealing approach for developing end-use load shape information is to collect the data directly by metering the desired end uses. Given the high cost of end-use metering (which should, but often does not, include the necessary costs of analysis following the collection of data), it has been impractical to carry out data collection for more than a small sample of the population. Efforts to reduce these costs and to increase the explanatory power of data already collected are the focus of future work.

Early Collection Efforts

The earliest efforts to collect end-use load shape data for utility planning date back to publications in the 1960s by the Load Research Committee of the AEIC. These studies of individual,

predominantly residential loads, such as electric water-heating and air-conditioning, were performed in support of utility electricity marketing efforts (AEIC 1974). In the late 1970s and early 1980s, these studies were joined by a host of individual building metering studies that were typically parts of larger research studies on the performance of conservation technologies. (A good summary of many commercial sector projects can be found in Heidell, Mazzucchi, and Reilly 1984.)

The distinguishing feature of these early studies is that they did not focus on the statistical generalizability of the results (which, by definition, could not be generalized to larger populations in the case of individual building studies). In large part due to the high cost of direct metering but also due to the fact that incorporation of the results into a utility planning process was never envisioned as part of the research design, these studies are of secondary importance for most utility planning purposes. Where some statistical sampling procedures did enter into the research design, as was the case for some of the AEIC studies, the age of these studies, some of which are close to 30 years old, makes continued use problematic.

State-of-the-Art Collection Efforts

More recently, electric utilities, realizing the value of end-use load shape data for planning purposes, have engaged in a number of end-use load shape metering studies. What distinguishes these studies is that the samples are often large, and, more importantly, use of the results for utility planning is an explicit and major justification for the projects.

We have identified 27 recent end-use metering projects in the United States (see Table 4-1). The list of commercial sector projects is felt to be reasonably complete and includes several projects just getting under way; however, the list of residential projects may reflect biases due to the authors' location in the western part of the United States. We are not aware of any industrial sector end-use metering efforts involving sample sizes approaching those of the projects in Table 4-1.

The first four columns of Table 4-1 describe the sponsor of the project, the geographic area under study, the project name, and the customer sectors. Note that several sponsors have more than one project (or one project that covers multiple segments of the residential, multifamily, and commercial building sectors). Multiple projects by a given sponsor are a testament to the increased importance these sponsors place on the use of metered data for improving planning assumptions and estimates.

Table 4-1. Recent major end-use metering projects.

Sponsor	Geographic Area	Project Name	Sector ^a	Sample Type ^b	# of Bldgs. Bldg. ^c	EU/ Total EUs	Protocol Type ^d	Quality Control ^e	Time Resol.	Dur. (Yrs.)	Status
Bonneville Power Administration	Hood R., Ore.	Hood River	RES	Retro/Stat	314	3	All EU-Sub	Limit	15 min.	5	Completed
	Pacific NW	RSDP	RES	Exp/Ctrl	422	3	All EU-Sub	Limit	Weekly	2	Completed
	Pacific NW	ELCAP-Base	RES	Statistical	288	8	All EU	Sumcheck	Hourly	5	Ongoing
	Pacific NW	-Case	RES	Special	56	8	All EU	Sumcheck	Hourly	5	Ongoing
	Pacific NW	-RSDP	RES/MF	Exp/Ctrl	155	8	All EU	Sumcheck	Hourly	6	Ongoing
	Seattle, Wash.	-Base	COM	Statistical	103	12	All EU	Sumcheck	Hourly	4	Ongoing
	Pacific NW	-CREUS	COM	Retrofit	40	12	All EU	Sumcheck	Hourly	4	Ongoing
Seattle City Light	Pacific NW	Energy Edge	COM	Experimental	28	7	All EU	Sumcheck	Hourly	6	Completed
Tacoma City Light	Seattle, Wash.	CHEBUS	COM	Retro/Stat	7	3	All EU-Sub	Limit	Hourly	6	Start-up
DOE & EPRI	Tacoma, Wash.	MRI	MF	Exp/Ctrl	100	3	All EU	Sumcheck	Hourly	1	Completed
Pacific Gas & Electric	National	AMP	RES	Statistical	150	6	All EU	Sumcheck	Monthly	2+	Start-up
	N. Calif.	MYCE	RES	Statistical	750	3	Select EU	Visual	30 min.	2+	Completed
	N. Calif.		COM	Statistical	45	5	All EU	Sumcheck	30 min.	2+	Start-up
So. Calif. Edison	So. Calif.		RES	Special	124	4	Select EU	Visual	5 min.	2+	Start-up
	So. Calif.		RES	Geographical	100	4	Select EU	Lim/Vis	5 min.	2	Start Up
Sierra Pacific	So. Calif.	RESA	COM	Geographical	53	4	All EU-Sub	Lim/Vis	15 min.	2	Ongoing
	So. Calif.	EIP-Res	RES/MF	Statistical	105	4	Select EU	Visual	?	?	?
	So. Calif.	-Com	COM	Statistical	105	4	Select EU	Visual	?	?	?
Wisconsin Electric	Illwaukee		COM	Statistical	50	4	Select EU	Visual	15 min.	?	Start-up
Northeast Utilities	Connecticut		RES	Exp/Ctrl	250	4	Select EU	Visual	15 min.	?	Start-up
Several utilities	Massachusetts	JUMP	COM	Exp/Ctrl	75	5	Select EU	Visual	15 min.	2+	Start-up
Ariz. Public Service	Arizona	LCEP	RES	Statistical	28	3	Select EU	Visual	?	?	?
Gulf States Utilities Co.	?		RES	Exp/Ctrl	100	3	Select EU	Visual	15 min.	2	?
Consolidated Edison	New York		RES	Special	232	4	All EU-Sub	Lim/Vis	?	?	?
State of Texas	Texas		COM	Statistical	396	2+	Select EU	Visual	?	?	Completed
Penn. Power & Light	Pennsylvania		COM	Retrofit	49	3	All EU-Sub	Lim/Vis	?	1	Start-up
	Pennsylvania		COM	Statistical							Completed

^a Sectors abbreviations: RES = Residential; MF = Multifamily; COM = Commercial. ^b Sample Type Abbreviations: Retro/Stat = Retrofit/Statistical; Exp/Ctrl = Experimental and Control (see text). ^c Average number of end uses per building (approximate); one may be by end use by subtraction for All EU-Sub. ^d End-use protocol type: All EU = separately metered; All EU-Sub = one by subtraction; Select EU = selected end uses/appliances only (see text). ^e Quality control abbreviation: Lim/Vis = Building total limit and visual reasonableness checks (see text).

Column five indicates the type of sample design used. Recall that the applications described in the first section provided two primary motivations for the designs of metered samples: (1) characterization of the building population for planning and forecasting purposes and (2) evaluation of the impacts of specific demand-side technologies or programs. Statistically based sample designs are generally used to obtain data in support of planning and forecasting processes. These designs are based on customer billing or survey data so that the metered buildings can be analyzed as representing a larger population. The use of metering to support evaluations of individual technologies or programs is typically based on a non-random sample of participants in the program, although some retrofit programs have relied on statistical sampling procedures. For new building programs, the samples are almost always a somewhat arbitrary (statistically speaking) set of experimental buildings from a pilot test of the program. Some of these projects will also include a parallel set of newly constructed buildings representing current practice as controls for the experiment. Other sample types indicated in Table 4-1 include studies of buildings selected for specific reasons such as high consumption or presence of particular appliances (termed Special) and studies that seek to capture geographical diversity within a region (termed Geographical). In general, these latter two sample types do not formally incorporate statistical sampling procedures.

Columns six, seven, and eight indicate the scope of the projects as measured by the number of buildings, average number of end uses per building, and total number of end uses metered.

Columns nine and ten indicate the monitoring protocol and primary method used for quality control by each project. The protocols used to define end uses are split into three groups: (1) those in which all defined end uses and a separate building total are metered (All EU), (2) those that meter at least the total and the major end uses but obtain the remainder by subtraction (All EU-Sub), and (3) those that meter only selected appliances or end uses in each building (Select EU). Among other things, the protocols determine the quality control procedures that may be applied. These procedures include a continuous energy balance using the building total as a sum-check, limit checks against monthly utility bills (if the remainder end use is small relative to the total consumption), and visual reasonableness and continuity checks when only selected end uses are metered.

Column eleven indicates the level of aggregation of the metered data. The time resolution of the data is typically 5- or 15-minute

intervals for regions where peak loads are the central planning issue, and hourly where annual energy is the primary concern (the Pacific Northwest).

Finally, columns twelve and thirteen indicate the duration of the projects and their current status if known.

Metering end uses for a large number of buildings is expensive. Costs depend on the level of detail called for by the measurement protocol and on whether economies of scale can be realized with a given sample size. Fully burdened costs for large, detailed, all end-use protocol projects including sum-check quality control procedures and a duration of two years are currently in the range of \$15,000–\$25,000 per commercial building and \$3,000–\$7,000 per residential building. The cost is split about equally between installation and maintenance, with the installation costs split about equally between hardware and labor. Importantly, these costs do not include the considerable effort required to develop software in order to archive and analyze the data.

These costs also mean that despite the explicit reliance on statistical techniques in some of the sample designs, the final samples are often not very large for a given stratum. As a consequence, the resolution of the analyzed data is often not very precise. For example, it is not uncommon to find that standard deviations across buildings for a given end use are equal to or greater in magnitude than the observed means. Statistically speaking, this means that the null hypothesis of the measured load being equal to zero cannot be rejected at the 95% confidence level!

Lowering the Costs of End-Use Load Shape Data Collection

The desire for increased statistical precision in end-use load shape estimates calls for research in three technical areas of end-use load shape data collection: sample size determination, project duration, and metering costs per end use. This need also justifies seeking less expensive means for obtaining end-use load shape data, such as the estimation techniques described in the previous section and, as we shall describe, the use of end-use load shape data collected by others (data transfer).

We are not aware of specific studies examining the issue of increased data precision as a function of sample size. We note from our experience, however, that mean end-use loads tend to stabilize with sample sizes of about 20. Nevertheless, even larger sample sizes may be required to explain observed variances. For example, some researchers have observed that some causal relationships,

such as the effect of number of occupants on water heating loads, can be obscured by other sources of variance when the sample size falls below 20 (Pratt et al. 1990). At the same time, other variance reduction techniques are possible. Others have suggested that it is possible to link small end-use metered samples with larger, whole-building load research samples to increase sample sizes, thus reducing variance, and thereby make end-use load estimates from very small samples representative of larger populations (Wright and Richards 1989).

On the issue of reducing the duration and cost of metering projects, there is evidence that the seasonal variation in nearly all residential and many commercial end uses (+10% to 20% of the mean) will preclude metering periods of less than a year from producing accurate results for some end uses (Pratt et al. 1990; Taylor and Pratt 1989). On the other hand, for some highly scheduled, non-weather-dependent end uses, such as commercial lighting and water heating, shorter duration metering periods may be warranted. At the same time, it should be recalled that the fixed costs of installing metering equipment are roughly half the total costs of metering (excluding analysis of the data) and that multiyear data also allow for study of price elasticity, occupancy and behavioral changes, retrofits and equipment changes, and persistence of savings from demand-side measures, among other topics.

More recently, efforts have been made to reduce the direct costs of metering end uses. One approach involves the use of decomposition techniques that track total electricity consumption at an extremely high level of time-resolution (about a thousandth of a second) in order to capture the signature of individual pieces of equipment turning on and off (Jones and Flagg 1989). Separate end-use loads are automatically detected by this decomposition, which in effect reduces the number of metering points per building to one. Another extremely promising approach involves the use of existing energy management systems as a direct source of equipment operating profiles (Flora, LeConiac, and Akbari 1986). (We also refer the reader to Harry Misuriello's review in this book of the state of the art in building energy performance monitoring.)

Using End-Use Load Shape Data Collected by Others

Perhaps the least expensive means for obtaining metered, end-use load shape data lies not with optimized sampling designs and better hardware, but with the transfer of results from existing metering studies. Prior to the recent era of end-use metering, which began around 1984, almost all utility applications of end-use load shape

data relied on either secondary or estimated data. Attitudes were pragmatic: some metered data, from any source, was considered better than none simply because one did not have the ability to judge these data independently.

In addition to the grey literature of utility reports on individual metering projects (see the references for a selective listing of the reports underlying the metering studies reported in Table 4-1), we are aware of few published end-use load shape data compilations. Notably, the Bonneville Power Authority (BPA) has produced two major compilations of end-use load shape data from its ELCAP project, one for the residential and one for the commercial buildings being metered (Pratt et al. 1989; Taylor and Pratt 1989). In addition, researchers have compiled and analyzed residential end-use load shape data collected by California utilities in order to provide inputs for the California Energy Commission's peak load forecasting model (Ruderman et al. 1989). Finally, there is a relatively new software package, RELOAD (SRC/LCA/BCD 1988), which is distributed with a library of end-use load shapes that have been drawn from a number of sources, including engineering simulation and end-use metering.

Today, the increasingly extensive geographic coverage of end-use metering projects suggests that an adequate range of climatic and cultural diversity may nearly exist to characterize the residential sector for most of the United States and that this will also soon be achieved in the commercial sector. However, the widespread availability of these data will hinge on resolution of two important institutional and analytical issues.

Institutionally, there remains the need to establish mechanisms for equitably sharing and promoting the use of this expensive resource. An important issue is the confidentiality and propriety of data from donor utilities. Currently an informal questionnaire is being circulated to potential users and suppliers of data to help define parameters for some form of institutional data sharing (BPA 1990).

Analytically, substantial issues regarding the transferability of data remain unaddressed. These issues include climate normalization, control for regional structural characteristics, and control for occupant characteristics. We presume that these factors are responsible for a large part of the observed variability of end-use load shapes, along with a number of as yet to be determined random factors. Analysis to determine the nature of the influence of these factors on load shapes, leading to methods to adjust and transfer load shapes, is straightforward conceptually but complex in practice.

shape development effort. It might consist of, first, metering targeted at market segments or technologies for which little or no data are available and, second, small end-use metering samples designed to be leveraged with less expensive survey and whole-building load data. For end-use data development efforts to reach this level of maturity, a number of activities must take place. These involve important synergisms, and would benefit greatly by proceeding jointly. The following three general recommendations illustrate the type of process that could take place over the next few years.

First, existing end-use metering projects should soon provide adequate coverage of the most important building types, end uses, and geographic regions. Efforts to more fully exploit these data sources should be a high priority for future research. The primary goal of these efforts should be to develop the analytical procedures necessary to permit meaningful transfer of load shape data from one utility service territory to another. The procedures must explicitly capture the causal relationships underlying observed load shapes in order to control for differences in climate, building characteristics, and occupant behavior between service territories. These analytical efforts should proceed in parallel with institutional efforts to facilitate data transfer in which issues of confidentiality and propriety of data from donor utilities must be addressed.

Second, end-use load shape estimation methods should be able to produce data of sufficient accuracy for utility planning purposes. In particular, there is great promise in the use of hybrid estimation methods, which combine the best aspects of simulations, statistical analyses, and measured data. Efforts to utilize recent end-use metered data to validate estimation methods should be given the highest priority for research. From the standpoint of improving the estimation methods, a major challenge lies in determining the optimal amount of non-load shape data collection needed to support load shape estimation.

Third, it is likely that the realization of these two research objectives, driven by increased utility applications for end-use load shape, will still call for end-use load shape metering efforts. These incremental efforts will be a healthy sign for load shape development efforts if coordinated with load shape data transfer and improvements in estimation methods.

The costs of developing load shape data for utility planning can be significant, ranging in descending order from end-use metering to estimation to data transfer. Yet the benefits from improved resource planning will easily outweigh these costs. The issue for future end-use load shape development is not one of whether, but of

how. We believe society will be best served when these efforts incorporate all potential sources of data including metering studies from other service territories, estimation based on utility-specific data, and local end-use metering. The challenges for future research lie in determining a cost-effective mix of these sources, not in choosing one over the other.

Acknowledgements

The study described in this chapter was funded by the Assistant Secretary for Conservation and Renewable Energy, Office of Utility Technologies, U.S. Department of Energy, under Contract No. DE-AC03-76SF00098.

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