An Evaluation of Residential Central Air Conditioner Load Data Transfer Methods

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Abstract: Hourly end-use load information is extremely useful to utilities for purposes of system planning and forecasting, demand-side management, and peak-load planning. Load data transfer—borrowing data from other service territories and/or time periods—is less expensive than direct metering. However, not much is known about the imprecision and statistical bias introduced by methods of load data transfer. We evaluate the accuracy of 11 low-cost load data transfer methods for residential air conditioner use. We use each method to predict load shapes which are then compared to a shared set of actual end-use measured loads. We conclude that the degree of imprecision and bias introduced by each method can be quantified, at least in a preliminary way, and that low-cost methods like the ones we evaluated may be cost-effective for the many purposes for which utilities use end-use load data.

Keywords: load modeling, residential air conditioning load data, end-use planning, end-use forecasting

I. INTRODUCTION

Cutting costs and retaining customers are two important business challenges for electric utilities in the late 1990s. The cost-effective acquisition and deployment of customer end-use information will figure prominently in meeting these challenges as utilities use these data to better understand customer energy demand.

Acquiring end-use metered load data presents a dilemma for utilities. On the one hand, there is little question of the value of knowing the timing and magnitude of end-use loads in customers' premises, for purposes of system planning, demand-side management, and planning for peak loads. Furthermore, the electricity industry is unique in its ability to gather information, through its metering system, on the consumption of its product on a fine time-scale and with a high level of resolution. On the other hand, collecting and analyzing end-use metered data is expensive. Costs have been reported from \$15-25k/building in the commercial sector to \$3-7k/house in the residential sector for long-term end-use metering projects. [3].[1] There have been only a handful of large, continuous end-use metering projects in the country; most projects involve very small samples or short metering periods [14].

From a business perspective, the critical question about acquiring end-use load data is: will revenues from use of end-use data exceed the cost of acquiring the data?[2] If the end-use data have a large impact on a costly decision such as reinforcing a substation, then it is worth spending more to get these data, and vice versa. Or if the cost of gathering end-use data can be reduced, utilities can more easily justify taking advantage of the wealth of information they represent.

This paper evaluates 11 low-cost methods of acquiring residential central air conditioner load data. Residential central air conditioning is often the dominant contributor to residential peak demands, and often dictates the timing and magnitude of system peak demands, as well. As a result, residential central air conditioner loads are of particular concern for system planning, demand-side planning and evaluation, and cost-of-service analysis.

The 11 methods evaluated here all involve modifying or adapting metered central air conditioning data originally collected in one service territory and transferring for its use in another service territory. We refer to these methods generically as load data transfer methods. Transferring load data is always less expensive than load metering. We focus specifically on the very lowest cost load data transfer methods, i.e., ones that do not require detailed demographic or engineering data; the most complicated methods rely on hourly weather data.

"Borrowed" end-use load data has long been used in the electricity industry; however, its use has always been accompanied by nagging concerns regarding the inevitable losses in precision and introduction of statistical bias

[1] These estimates represent fully burdened costs for large, detailed, two-year end-use protocol projects including sum-check quality control procedures. The costs are equally split between installation and maintenance; installation costs are equally split between hardware and labor. Importantly, these costs do not include the considerable effort required to develop software to archive and analyze the data.

[2] See [6, 8] for illustrations of decision-analytic approaches to ration end-use and load research data resources, which evaluate these trade-offs systematically.

associated with using data not from the borrower's service territory.[3] The goal of our work is to represent the performance of load data transfer methods so that potential users can assess the precision of these data and thus the cost effectiveness of using them. An important motivation for our decision to examine comparatively low-cost data transfer methods is our conviction that, in the right circumstances, low-cost methods may be the most cost-effective source of end-use load information. To demonstrate this point, we create a controlled set of conditions that permit us to evaluate directly the precision of data transfer.

The paper is organized in four sections following this introduction. In Section II, we describe a testing procedure that we developed to evaluate the performance of the load data transfer methods; this procedure involves comparing loads predicted by each method to a reference set of loads that were developed from end-use metered data. We define several measures to capture different aspects of the performance of the methods. In Section III, we describe the 11 residential central air conditioner load data transfer methods that we evaluated. In Section IV, we present our findings and describe the relative accuracy of the types of methods. Section V summarizes our findings.

II. EVALUATING THE PERFORMANCE OF LOAD DATA TRANSFER METHODS

The desire to avoid costly metering has always been a strong motivation for borrowing or transferring load data from elsewhere. Evaluating the performance of load data transfer methods is difficult because the actual loads that the transferred data will be used to represent are, by definition, unknown. In other words, there is no standard by which one can assess the precision and bias of different load data transfer methods. (This limitation can also extend to direct metering unless methods are devised for using metered data in real time.) In this section, we describe a simple procedure for evaluating the performance of end-use load data transfer methods and introduce measures to evaluate different aspects of the performance of the methods.

Our evaluation of the performance of the load data transfer methods consists of using each method to "predict" hourly loads for regions for which we have separately developed known, reference load shapes from metered data. These reference load shapes were developed from metered data collected during a five-year period from 350 central air conditioners located in three California regions: Fresno, Sacramento, and San Jose [2]. We created a single hourly load shape for each region (and each year) by aggregating and averaging the metered data within each region [5].

Some of the models were estimated using data from the same regions upon which they were then tested. We estimated these models using only the first two years of load shape data from the five-year project. For all models, our "test" consisted of comparing predictions for the final three years of load shape data. Thus, we avoided "testing" the models on their ability to predict data that they already incorporated.

There are many ways to measure the performance of load data transfer methods. Because our goal is to determine the usefulness of transferred load data, we developed three measures of performance that capture information of key importance to utilities' system planning/forecasting, demand-side planning and evaluation, and cost-of-service analysis. These three measures are: (1) daily energy use, (2) daily peak load, (3) load at 4 PM. See Figure 1. The importance of each measure, of course, will depend on the specific application of the load data; measures that are important for one application may be less important for other applications.

The first measure, daily energy use, indicates how well a load data transfer method predicts energy use for each day of the forecast period (three summer seasons). In other words, for our study this indicator measures how well the methods predict total air conditioning energy use during three summer seasons. The accuracy of such transferred end-use energy consumption data is important in determining the usefulness of the data for purposes of system planning/end-use forecasting, demand-side program planning, and demand-side program evaluation.

Our second measure, daily peak load, is a partial but important indicator of how well the methods predict daily load shape. This measure is important for demand-side program planning and program evaluation. It is less important for system planning because the peak load for an end-use may not be coincident with system-wide peak demand.

The third measure, load at 4 PM, is a proxy for measuring the contribution of an end use to system-wide coincident peak demand—many utilities record system peak demands during the later portion of hot summer afternoons. Coincident peak demand is of extreme importance for system planning/forecasting, local area reliability evaluation and planning, and cost-of-service studies.

III. RESIDENTIAL CENTRAL AIR CONDITIONER LOAD DATA TRANSFER METHODS

In this section, we define three categories of load data transfer methods and classify the 11 methods we studied. We refer to the source of the original load data as the donor, and the region to which the data are being transferred as the recipient.

A. Categories for End-Use Load Data Transfer Methods

The first and least expensive class of load data transfer methods uses a donor's load data without any adjustment.

[3] These concerns should surface whenever new data are incorporated into business decisions. An objective of our work is to demonstrate that these concerns can be addressed systematically, regardless of whether the data are borrowed or developed in-house.

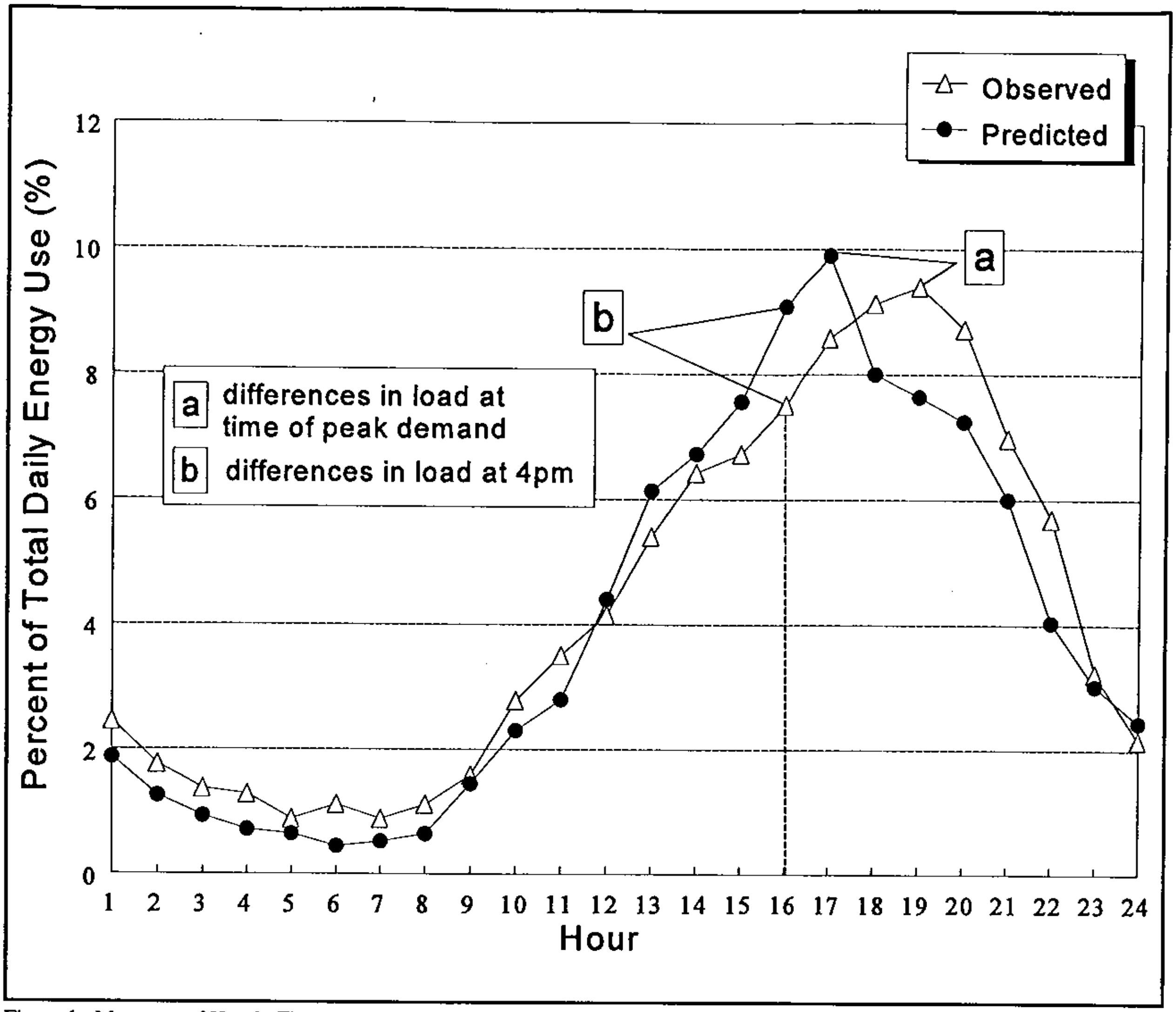

Figure 1. Measures of Hourly Fit

These methods can be as simple as digitizing end-use load shapes from reports summarizing the results of end-use metering studies. We refer to these as "pure" or *non-model-based transfer methods*. Several of our examples were of this type.

The second and third classes of methods both involve the development of models (rather than actual load shapes) from the donor's load data; the models are then used, along with non-load information from the recipient, to predict loads for recipient. Use of a model to decompose and/or systematically relate load shapes to non-energy use data (such as hourly weather) allows introduction of recipient-specific information, which, ideally means more accurate load shapes.

In the second class of methods, models are developed using only weather information from the donor's and recipient's service territories. We refer to these methods as *weather-based-transfer methods*. The bulk of our evaluation focuses on examples of this type of method.

The third class of methods comprises models based on weather, demographic, and engineering information from both

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demographic, and engineering information from both the donor's and recipient's service territories. Sophisticated statistical analysis may be involved [15, 16]. The methods can be used to develop separate models for individual households [11], which would then be followed by detailed matching of similar households between donor and recipient service territories. The collection and analysis of engineering and demographic information greatly increases the cost of this method compared to the previous two. We did not examine examples of this type.[4]

B. *Eleven Low-Cost Residential Central Air Conditioner Load Data Transfer Methods*

The 11 residential central air conditioner load data transfer methods we examined are listed in Table 1.

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4 Although this is strictly true, two of the models implicitly control for the demographic and engineering characteristics of the donor and recipient utility service territories in a way that is actually superior to what is offered by models in this third class of methods.

TABLE I
ELEVEN RESIDENTIAL CENTRAL AIR CONDITIONING LOAD DATA TRANSFER METHODS

Load Data Transfer Method	Type and Description	Source of Donor Load Data
RELOAD	Non-model	Southern California [13]
CEED1, CEED2	Non-model	Southern California, unknown
CEEDw	Weather-model: adjustments based on dry-bulb temperature	Southern California
Quantum	Weather-model: 24 hourly regressions, based on dry-bulb and wet-bulb temperature [12]	Pacific Northwest [1]
LBL1SJ, LBL1S, LBL1F	Weather-model: 24 hourly regressions, based on four weather variables [4]	Northern California (San Jose, Sacramento, Fresno) [4]
LBL2SJ, LBL2S, LBL2F	Weather-model, 2-stage: daily energy based on up to six weather variables; fixed hourly load shapes selected based on dry-bulb temperature [4]	Northern California (San Jose, Sacramento, Fresno) [4]

RELOAD—RELOAD is a software system for the management and manipulation of load shape data [10]. RELOAD includes algorithms to estimate end-use load shapes, a variety of tools for editing and redefining load shapes, and a collection of default load shape data for a variety of end uses in the residential, commercial, and industrial sectors. The default load shapes are based on metered loads from a number of end-use metering projects conducted across the United States and are provided as a single, representative hourly load shape for each end use. We examined the default load shape for residential central air conditioning. In other words, a single, un-adjusted 24-hour "typical" load shape taken from the RELOAD library of end-use load shapes was compared to metered daily load shapes for each of day of three summers.

The default RELOAD residential central air conditioning load shape was developed from five-minute-interval, metered data collected in 1987 from 62 single-family, detached residences in the Southern California Edison (SCE) service territory [13]. The SCE service territory encompasses most of Southern California.

A "pure" load shape data transfer method such as RELOAD must address many potentially significant sources of bias, including differences in: the physical features of household, weather conditions, air conditioning equipment, and operational behavior. In our study, it is possible that these biases might not be a significant concern because the donor and recipient service territories are adjacent (although the data were collected in different years). Nevertheless, it is impossible to generalize from our findings to other cases.

CEED—The Center for Electric End-Use Data (CEED) is a clearinghouse for end-use load and energy information [7]. CEED's data request service (DRS) collects end-use metered data from metering projects around the country and provides these data and related information on a fee-for-service basis. DRS can customize data in a number of ways including selecting, reaggregating, and rescaling.

CEED's DRS provided us with three sets of hourly end-use load shape data. The first two sets of data, called CEED1 and CEED2, are similar to the RELOAD data set in that they are also examples of a "pure" load data transfer method. Both are a single unadjusted, average daily load shape consisting of 24 separate load values developed from two different load metering projects in the CEED library. CEED1 was, in fact, developed from data collected by the same metering project that provided the data used to develop RELOAD. The difference between CEED1 and RELOAD is that the CEED data were developed from a larger sample of residences than the data used to develop RELOAD.

A third set of data, called CEEDw, was developed specifically for our project. We provided the DRS with hourly weather data from the three regions in our study and asked for separate representative hourly load shapes for each region for each day of the three summers for which we had metered loads to compare CEEDw against. DRS created CEEDw by adjusting CEED1 using these hourly dry-bulb temperatures to rescale loads from their library of metered loads. Specifically, the DRS performed 24 separate regressions – one for each hour of the day - on a composite derived from their library of donated loads and hourly dry-bulb temperatures associated with these loads. The DRS then introduced the hourly dry-bulb temperatures from the three summer forecast periods (i.e., the recipient's weather) and produced a predicted value for each hour of these three summers. CEEDw, therefore, represents a weather-model-based data transfer method, according to our classification of models. CEEDw attempts to address differences in weather and location between the donor and recipient but does not explicitly address other potentially important differences in the characteristics of the two donor and recipient populations, such as household size.

Quantum—Quantum Consulting developed a series of end-use load shape data transfer models for use in a recent technology assessment project [12]. As with CEEDw, the central air conditioner model consists of 24 individual regressions, one for each hour of the day. Unlike CEEDw, the explanatory variables included both hourly dry- and wet-bulb temperature. The hourly metered data used in these models were collected by the Bonneville Power Administration as part of the ELCAP project [1].

Like CEEDw, the Quantum method attempts to address differences in weather but does not explicitly address other potentially important differences in the characteristics of the donor and recipient populations, such as housing thermal properties or occupant behavior.

LBL One- and Two-Stage—The last two models we analyzed are based on methods supported by an hourly electric load model called HELM [9]. HELM operates as a post-processor for separate, stand-alone annual energy forecasting tools; that is, HELM takes, as input, forecasts of annual energy use and then allocates the energy to the hours of the year. For space conditioning end uses, HELM offers a choice of two models. Three versions of the two models were estimated using the reference load shapes for three geographic regions: San Jose (SJ), Sacramento (S), and Fresno (F).

The first model, called one-stage (LBL1), is similar to Quantum in that it consists of 24 separate linear regression models (one for each hour of the day). However, the models were estimated using four variables (rather than two as in Quantum). After some experimentation with various possible explanatory variables, the models were estimated using: 1) a degree-hour version of the temperature- humidity index, base 68; 2) a summation of the prior six hours of this index; 3) the square of this index; and 4) a dummy variable for day-type (weekend versus weekday).

The second model, called two-stage (LBL2), is also based on separate models for two types of summer days [4]. However, the model for each type of day consists of two sub-models. First, total daily energy use is estimated with a linear regression model based on six weather variables (which is the maximum permitted by the HELM model). The variables for each model were selected from among a list of over 30 possible explanatory variables, all of which were based on dry-bulb temperature and relative humidity (e.g., average daily values, minimum value, maximum value, degree-days to various bases, etc.) The variables were selected to maximize the explanatory power of the daily energy model; accordingly, the variables selected and their coefficients vary by region, season, and day-type. Second, daily energy use is allocated to the hours of the day using a fixed load shape. The fixed load shape is selected from a set of six load shapes that are developed separately for each type of day. The criteria for selecting among the fixed load shapes is based on a single daily weather variable (e.g., average dry-bulb temperature). Hence, if the daily weather observation falls within a particular range, the hourly weights associated with a particular fixed load shape corresponding to this range are used to allocate total energy to each hour of the day.

We will look closely at the accuracy of these last two models when they are used to predict loads for the regions upon which they are based, because these results will be indicative of the upper limit in performance one could expect from a load data transfer model. That is, in these instances, the recipient and donor are identical. Specifically, the models are estimated using the first two years of reference load shapes developed for each of the three regions. They are then used to forecast or predict load shapes for the final three years of reference load shapes for the same region. Because LBL1 and LBL2 were estimated using data from the same areas for which load shapes were then forecasted, the models' predictions will represent the best possible performance of the second class of models. That is, the two models, when used in this way, implicitly control for all differences (e.g., in housing thermal properties and, to a lesser extent, occupant behavior) with the exception weather. They are, in this regard, representative of the type of performance one might expect from the third class of models we defined, in which differences in building characteristics and occupant behavior are explicitly accounted in addition to weather. We will refer to these two models, in which the recipients and donors are the same, as "idealized" methods.

IV. FINDINGS

Our findings were generally consistent for our three study regions, so we describe detailed findings for only one region, Fresno, shown in Figure 2. This is the hottest of the three regions examined. For each of the three measures of performance (daily energy, peak demand, and load at 4 PM), we present the distribution of errors (i.e., the difference between predicted and actual loads) for each model.

The distributions follow a standard format. Starting from the middle, the median is represented by a hollow line and the ends of the shaded box represent the upper ends of the first and third quartiles of the distribution. The shaded box represents the range in which half the errors lie. The t-bars at the top and bottom of the plots represent a distance of 1.5 times the interquartile range and thus include most of the errors. Individual errors greater or less than 1.5 times the interquartile range are reported individually as extreme values outside the t-bars.

A median value far from the horizontal zero line is indicative of significant deviation (bias) in the model's predicted value compared to the metered value. Wide t-bars are indicative of substantial spread in the errors, i.e. substantial imprecision. Other things being equal, less bias is preferable to more, so the median value should be close to zero, and more precision is preferable to less, so the t-bars and upper and lower edges of the shaded box should be tightly clustered around the median.

We review the findings by answering three questions: (1) How do the findings vary depending upon which of the three measures of performance is considered? (2) Which methods are more biased/more precise? (3) How well do the so-called "idealized" methods, which were estimated using data from a given region, perform in predicting loads for this same region (LBL1F and LBL2F).

We find that the results are substantially though not completely consistent for the three measures of performance. That is, if a method is biased in one direction or is comparatively more or less precise for any one measure, it is also likely to exhibit the same characteristics for the other two measures. This tendency is most pronounced with regard to each model's precision but is still generally true for its bias.

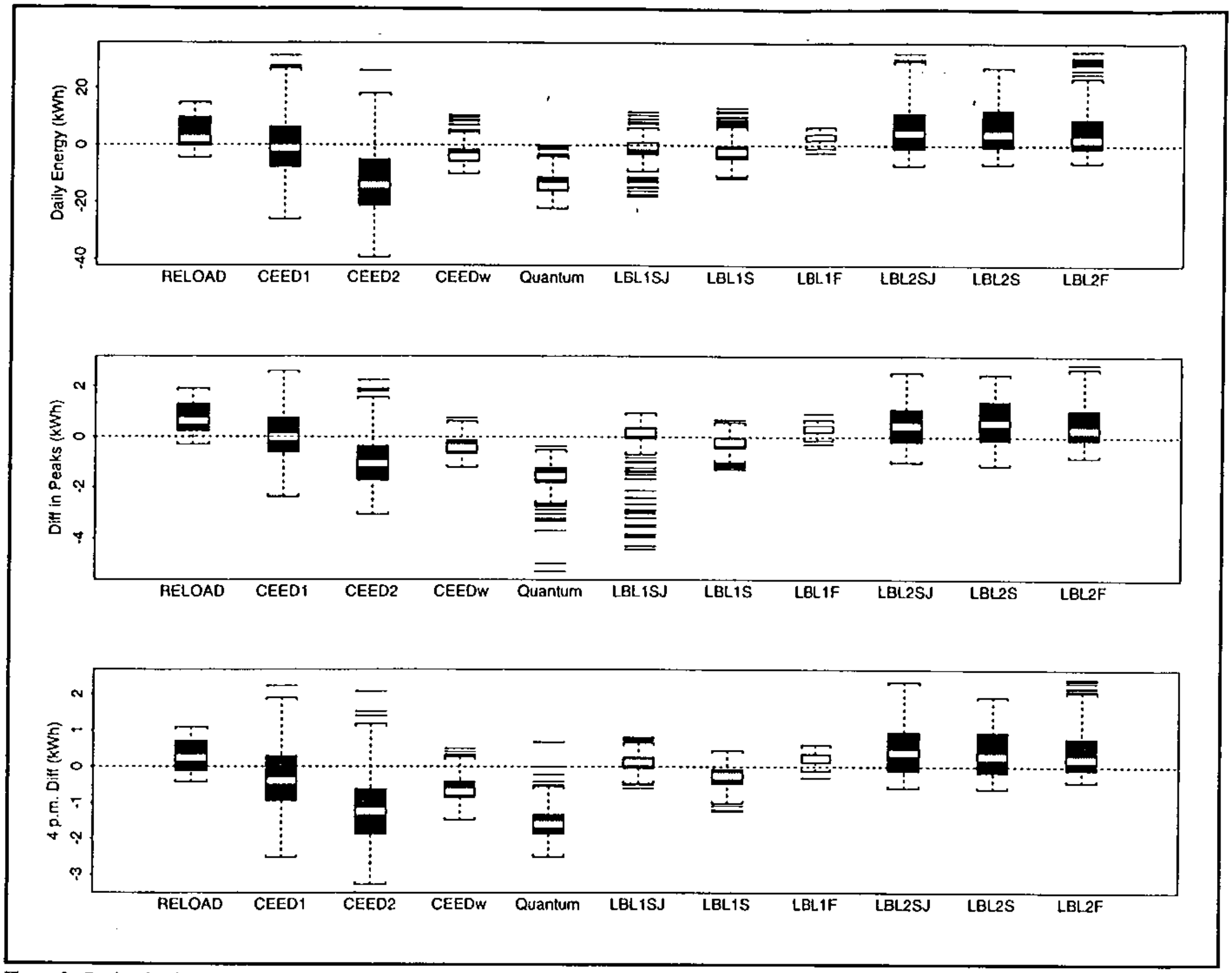

Figure 2. Region 3—Summer 1987 to 1989

We conclude that the weather-model-based methods generally perform better than the pure or non-model-based methods. In particular, the weather-model-based methods appear to be far more precise than the non-model-based methods. An exception is the LBL two-stage models, which are as, or more imprecise than the non-model-based methods. The methods all show some degree of bias.

Among the non-model-based methods, the performance of RELOAD is striking because its precision is high compared to CEED1 and CEED2. Among the weather-model-based methods, the three LBL one-stage models (LBL1SJ, LBL1S, and LBL1F) perform fairly consistently (small bias, higher precision), compared to CEEDw (greater bias, similar precision) and Quantum (greater bias, lower precision). As mentioned, the three LBL two-stage models (LBL2SJ, LBL2S, and LBL2F) are noticeably less precise than the other weather-based models.

Finally, it is instructive to examine the performance of LBL1F and LBL2F, which were estimated using the same reference load shapes (although from different years) to which they are being compared. The results obtained using these models represent what is likely to be the best performance that might be expected from even more sophisticated models or even from direct metering. As might be expected, LBL1F is the most precise of all the methods considered; however, there is still noticeable bias in the results. Other methods showed lower bias but lower precision. LBL2F's bias is comparable to that of LBL1F (small, but still noticeable), yet LBL2F is far less precise.

V. CONCLUSIONS

We have developed and applied a straightforward test to evaluate the performance of 11 methods for developing residential air conditioning load shapes using borrowed data.

The methods ranged from extremely low-cost ones involving no adjustment of borrowed data to slightly more expensive ones that involved developing simple statistical correlations between borrowed data and hourly weather data. All the methods are significantly lower in cost than direct metering. We were able to estimate two "idealized" models using data from the same region for which the test was conducted; we argue that the results from these models most likely represent the best performance that could be expected even from more sophisticated data transfer methods and or direct metering. We found that weather-based models generally performed better than non-weather-based models. One of the idealized models performed slightly but not dramatically better than the other weather-based models; the other idealized model performed slightly worse.

We recommend that choices of methods to develop end-use load information should consider the cost of obtaining the information relative to the value of the decisions that the information supports. No method is free from error or bias. The importance of error and bias should not be evaluated in the abstract, however, but instead relative to available alternatives. By demonstrating that relatively low-cost methods for borrowing or transferring load shape data have comparable performance to what can be expected from more expensive methods, we conclude that relying on low-cost methods may be a highly cost-effective alternative relative to using more expensive methods, such as direct load metering.

VI. ACKNOWLEDGMENTS

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