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THE LBL RESIDENTIAL ENERGY AND HOURLY DEMAND MODELS

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ABSTRACT. The LBL Residential Energy and Hourly Demand Models provide forecasts of energy consumption and hourly demands by end-use. We applied these models to five electric utility service areas. Reasonable agreement with historical residential sales (within 5%) and hourly demands (within 15% on peak) was obtained over several years of data. These models offer: (1) end-use economic response (fuel choice and usage); (2) end-use engineering detail; (3) separation of customers into rate classes; (4) integration of residential sales and hourly demand projections; and (5) capability to analyze demand-side impacts.

1. INTRODUCTION

A methodology has been developed for simultaneously forecasting residential electricity sales and hourly demands by end-use. This method has been applied to five electric utilities, and provides detailed analyses of the end-use components of load growth, and potential effects of end-use-specific conservation programs for each hour of a 20-year forecast. Changes to the load shape due to changes in the appliance mix within households (including interfuel competition), efficiency improvements due to market forces, and changes in usage behavior in response to changing economic conditions are captured.

The LBL Residential Energy Model [1] was developed to provide policy analyses at the end-use level for the U.S. Department of Energy [2]. The model utilizes a data base of engineering estimates (equipment costs and energy consumption of alternative designs of each product), and economic elasticities (fuel choice, efficiency choice, usage behavior, thermal integrity of buildings) and produces a 20-year forecast of residential energy consumption in the US. The end uses considered are: space heating, air conditioning, water heating, refrigerators, freezers, cooking, clothesdryers, lighting, and miscellaneous.

A second model - the LBL Residential Hourly and Peak Demand Model [3] - was developed to provide hourly residential demands, consistent with the annual electricity sales projection. The hourly model contains diversified hourly load profiles for each end-use. Space heating and air-conditioning are climate sensitive, as well as dependent on the hour of the day. The two models together provide an integrated forecast of residential electricity sales and peak demand, including end-use detail throughout [4-7]. Figure 1 gives an example of the end-use detail in the model output.

2. DATA AND METHODS

Most utilities can provide data about the number of residential customers, appliance holdings of their customers, and annual electricity bills (consumption and cost). Disaggregation of residential consumption into end uses is accomplished using utility data where available, or appropriate values from the LBL Residential Energy Data Base. Some elements of the national data base

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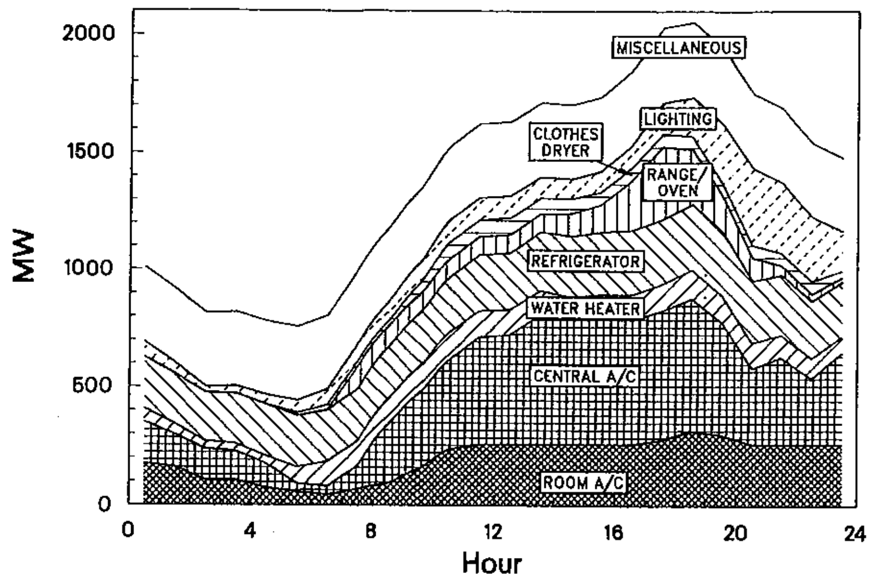

Figure 1. Residential Hourly Load Profile with End-use Composition.

[1,2] are used for all utilities, such as the engineering data for alternative appliance designs, and elasticities characterizing economic responsiveness. (In future, we hope to analyze economic responsiveness specific to different regions of the US.)

The analysis method is comprised of two parts: historical simulation and projection. Historical simulation involves the following steps:

1. *Build the data base.* Historical utility data is used to the maximum extent, and gaps are filled with other sources, including the LBL national data base.
2. *Benchmark residential sales.* A year is selected in which good historical data exists. The disaggregated representation of energy consumption by end-use is made to agree with total annual residential sales. (The "miscellaneous" end-use provides fine tuning.)
3. *Display seasonal sales.* The LBL Hourly model distributes electricity consumption over the hours of the year. Monthly sales from the model are compared with observation. Unit energy consumption for selected end-uses can be adjusted if necessary for better agreement.
4. *Compare hourly profiles.* The observed residential load profile (e.g., megawatts by hour of the day on peak days) is compared with the model simulation. Weather-sensitive end-uses are adjusted to account for region-specific thermostat settings; air conditioning thermostats are often set according to customer comfort, which takes into account humidity and perhaps building balance point. (Fine tuning can be done with the shape of "miscellaneous" demand, but we usually forego this adjustment.)

A comparison can be made at this point of the historical residential sales data and the modeled consumption, which includes end-use detail for one year.

The steps for obtaining a projected time-series of model results are:

1. *Gather exogenous variables.* We use data from the utility as much as possible for projected number of customers, energy prices, income, and sometimes appliance holdings. Other sources of data are used as needed.

2. *Use national elasticities.* The responsiveness of the market with regard to appliance efficiency, market shares (fuel choice), and usage behavior are taken from the LBL national data base. (In future, we hope to explore regional variations in these responses.)
3. *Recent years provide a "backcast."* We produce a backcast by starting the model in a past year (e.g., 1977), and using historical values for the independent variables, such as energy prices, household income, and weather, for the intervening period (e.g, 1978-1985). If the model design captured all the pertinent relationships correctly, then the output would exactly match historical observations of residential electricity sales and loads for the years up to the present. *
4. *Project future sales.* Providing the model with values for the driving variables (energy prices, income, customers) is sufficient to produce 20-year projections of residential sales. The model results can be compared with utility projections based upon different models.
5. *Simulate alternative scenarios.* By changing some of the assumptions, the effects of utility or government programs affecting individual (or groups of) end-uses can be simulated. For example, if building codes are altered to require different energy-consuming characteristics of new buildings, the effect on sales can be estimated. Similarly, the effects of mandatory efficiency standards on equipment can be assessed relative to the base case.

Figure 2 displays the results of modeling alternative scenarios for a future peak summer day. The top curve is the projected hourly demand in the base case. The next curve, only slightly different, shows the effects of a set of federal appliance efficiency standards. The bottom curve illustrates the peak savings due to an additional requirement that new central air conditioners be efficient. +

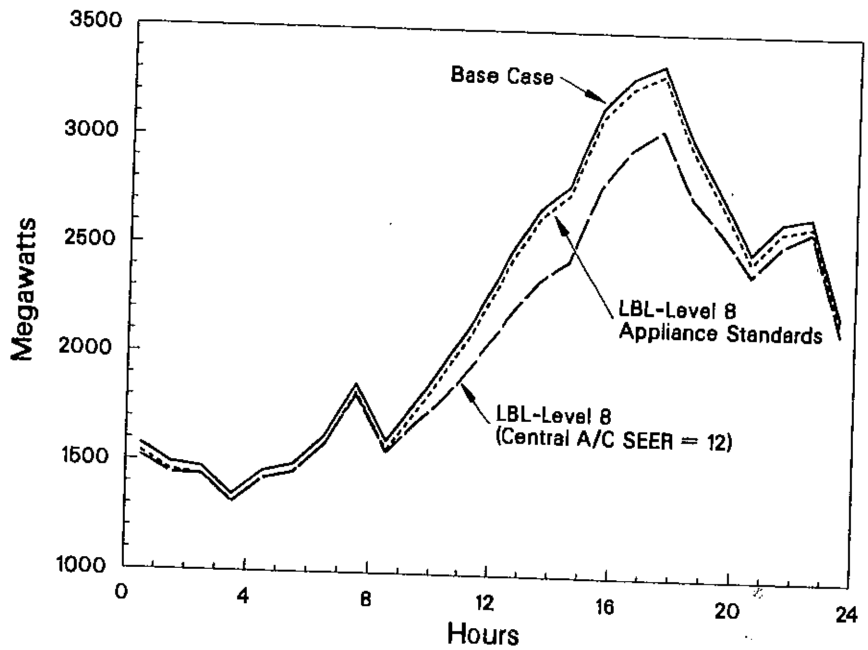

Figure 2. Predicted summer peak residential demands under different policy assumptions.

Financial impacts on utilities of load shape changes are described elsewhere [5-8].

3. RESULTS

Using a combination of utility data and the LBL national data base, representations of residential electricity consumption according to end-use and hour of the year have been created for five utility service areas: Detroit Edison Company [5], Virginia Electric Power Company, [7] Pacific Gas and Electric Company, [6] Nevada Power Company, and Texas Power and Light (a territory within the Texas Utilities Electric Company). We have gained considerable experience in the pitfalls of reported data, as well as the difficnlties of modeling. A few of these experiences are highlighted here.

3.1. Annual Residential Sales

A backcast for one utility is shown in Figure 3. Residential electricity sales simulated by the LBL models are within 2% of actual sales each year from 1978 to 1982. The economic recovery of 1983 boosted sales, in constrast to the model result of continuing decline. Since 1983, sales have declined at a rate slower than predicted. The difference between modeled sales and actual, as a percent, was 5.6% in 1983, and 8.3% in 1985.

We have examined indicators of sales of retail goods, which also rebounded in 1983. The economic indicator in the model, namely disposable income, failed to capture the full response of energy consumption to short-term economic cycles.

A forecast made by the utility for residential sales after 1982 expected continued growth, and underestimated the increase in 1983. On the other hand, the LBL simulation, while also underestimating 1983 sales, correctly predicted a declining trend in sales, due to increasing equipment efficiency and declining market shares for electric space and water heating.

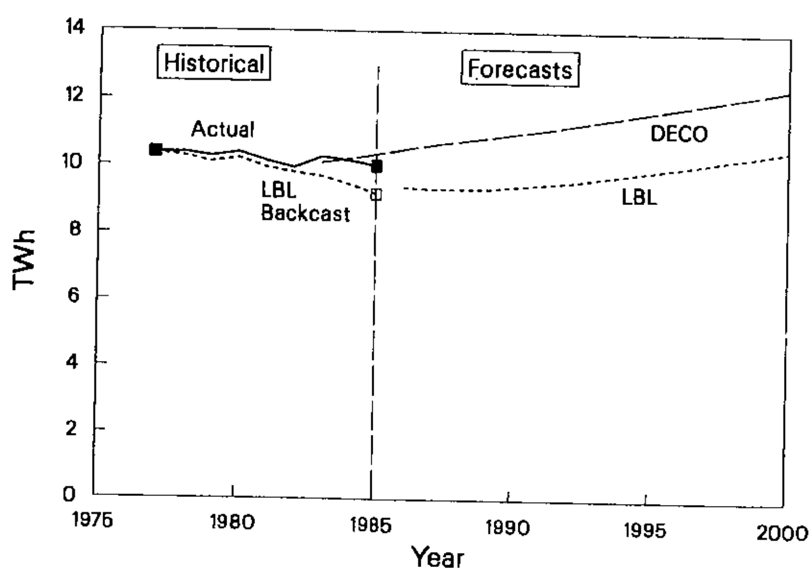

Figure 3. LBL Model backcast compared with Detroit Edison Company data and forecast.

3.2. Seasonal sales

After normalizing annual sales, we can examine monthly sales to determine the extent to which our models account for the seasonal variation in sales. Figure 4 shows the comparison of model results and reported data for one utility. The LBL model results were in best agreement with utility data in winter, with no clear pattern of over- or under-forecasting. The model overforecasts sales in spring and fall (the worst months show errors of 19% and 13%, respectively), and underforecasts sales in summer (the worst error is 14%). At least part of the explanation seems to be in the characterization of air conditioning patterns, as discussed in the next section.

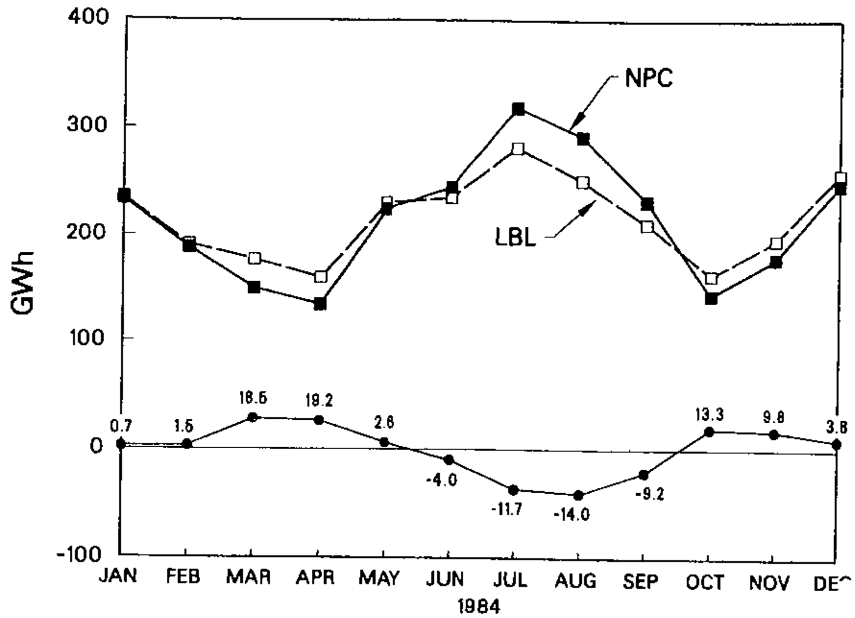

Figure 4. Monthly residential electricity sales: LBL model and Nevada Power Company data for 1984.

3.3. Hourly and peak demands

Simulating the demand for a single hour is more difficult than simulating annual sales. The variability in an hour is much greater than in the sales summed over a year. Nonetheless, the peak demand is a critical variable in utility planning. Capacity requirements are strongly dependent on the maximum demand that is expected on a system.

Figure 5 shows a comparison of model results for 12 monthly peak days for one utility. First, note that the model gives good agreement for the maximum demand of the year, in July. The agreement between model and data for peak demand is within 3%, better agreement than the monthly sales. Second, note the large overestimate of demand in May. The LBL model forecasts significant air conditioning demand on the first hot days of the year, but actual usage is much lower than would be expected from the temperature alone. Apparently, if the first hot day occurs in spring, people tend to use their air conditioning much less than if those same temperatures were to occur in August. This may also explain the overestimate of spring electricity sales by the model.

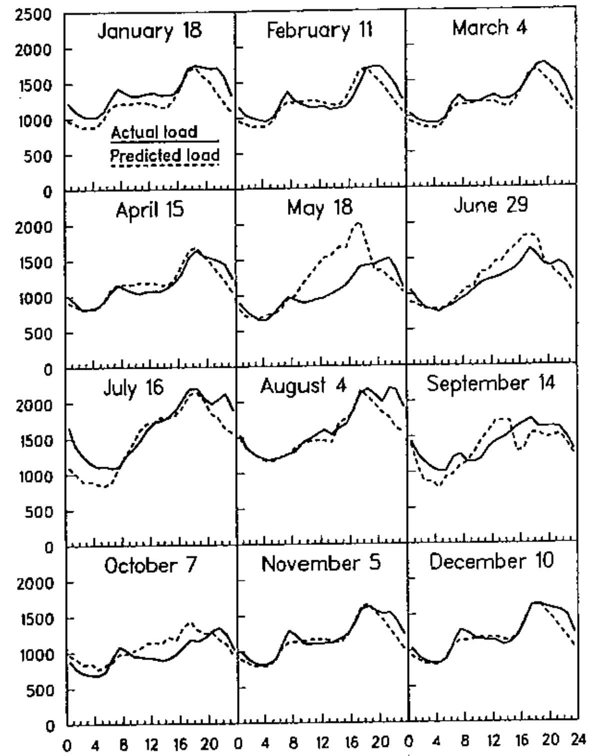

Figure 5. Monthly peak loads, 1982. LBL model and Detroit Edison Company data.

Figure 6 shows a different presentation (for another utility) of the monthly peaks. Here again, the agreement with the maximum demand is quite good, but a hot day in spring (April in this case) gives a model estimate of the peak demand that is much higher than the observed demand.

4. CONCLUSIONS

The LBL Residential Energy and Hourly Demand Forecasting Models give good agreement (within 8%) with historical residential electricity sales and hourly demands (within 15% on peak). The end-use detail of the models is useful for identifying the key components contributing to increasing (or decreasing) electricity sales and peak demands in future. This exercise revealed several difficulties in matching historical values. (1) Historical data, especially residential load profiles, may not be well known. (2) Data limitations, especially end-use load profiles, are a constraint on the model. Also, a typical "miscellaneous" load profile is difficult to define. (3) A method of accounting for regionally different responses to weather had to be developed.

4.1. Simulation of recent annual residential sales

Typical backcast results are within a few percent (< 8%) of observed annual residential electricity sales. The model results usually capture the up- and down-turns of the real world. However, sharp turns in short-term economic cycles are not always captured by the model, whose parameters are based more on long-term responses.

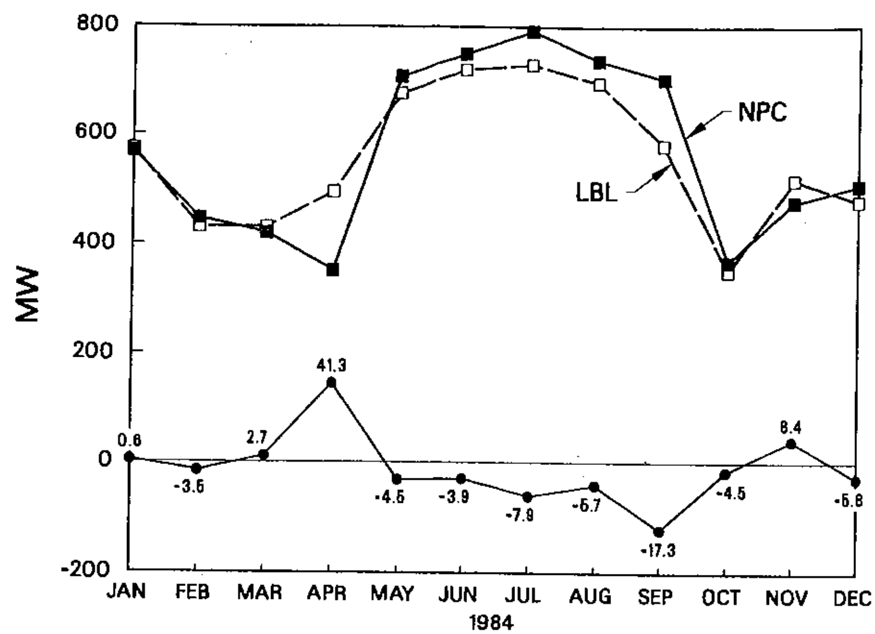

Figure 6. Monthly peak residential demand: LBL model and Nevada Power Company data for 1984.

4.2. Seasonal and hourly demands

Seasonal sales of electricity are modeled reasonably well, but there is some indication that air conditioning is more sharply concentrated in the summer, and damped in the spring, than the weather alone would imply.

Hourly and peak demands are the most difficult to reproduce with a model, since the variation in demand in an hour can be substantial. The general shapes of the hourly load profiles are in rough agreement with reported data for two utilities.

The results of LBL models for residential hourly load profiles are typically within 15% of the reported values in summer, and within 5% in winter. Significant overestimates (over 40%) of actual loads occured in some hot spring days apparently because much less air conditioning is used than the model expects based on the high temperatures.

4.3. Future sales

Comparing predicted sales, the LBL model often forecasts lower sales than utility projections because: (1) many utility projections fail to adequately account for the improving efficiencies of appliances; (2) differences exist between the LBL model and utility expectations regarding the penetration of electric space heating systems; (3) the LBL projection does not display inordinate growth in the "miscellaneous" category, while some utilities expect significant growth due to unidentified future electronic products.

4.4. Limitations

The agreement within 15% for the peak seasons seems good, in light of several limitations on the models: (1) It is inherently more difficult to model the electricity demand by hour; the variability in a particular hour is much greater than the variability in one year of cumulative electricity sales. (2) Only limited data exists describing the load profiles by end-use; if the occupancy or usage patterns of households differ significantly from one region to another, or from year to year, then the typical load profiles used by the LBL model may be in error for a particular utility. (3) The weather responsiveness of heating and air conditioning varies by region; temperature and humidity must both be considered, and building balance points vary by region.

4.5. Future work

The integrated forecast provided by these two models can be used to simulate the simultaneous effects on residential electricity sales and hourly demands of demand-side programs, or of penetration rates of new technologies. The range of error of these models is small enough to offer promising applications. Work is progressing to further reduce the uncertainty in these simulations.

* A successful backcast provides confidence in the model methodology. Of course, the ability to successfully match history serves only as a starting point. The forecaster must also consider how future economics, technologies, and behavior may differ from recent experience.

+ Seasonal Energy Efficiency Ratio (SEER) = 12.

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