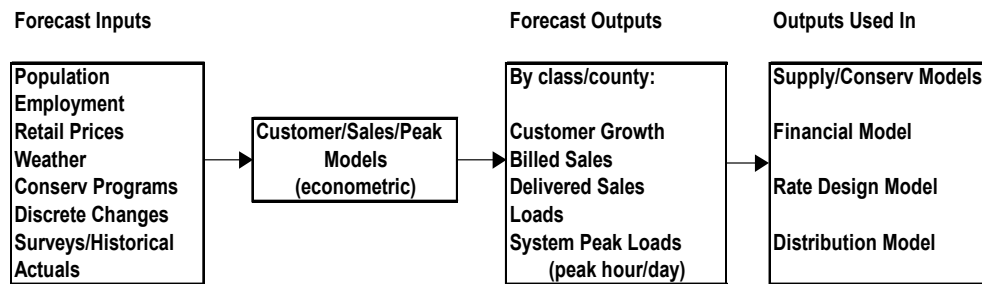


Load Forecasting Models

This appendix provides a more detailed technical description of the three econometric methodologies used to forecast (a) billed energy sales, (b) customer counts, and (c) system peak loads for electricity and natural gas. It also describes the methodology used to project hourly distribution of electrical loads.

For the 2007 IRP, we updated our key forecast driver assumptions and re-estimated the main equations. Key enhancements to this model are the ability to develop monthly sales forecasts using actual weather over the last 30 years, and to project loads at the county level. The diagram below shows the overall structure of the analysis.

**Figure H-1
Econometric Model for Forecasts
of Energy Sales, Customer Counts and Peak Loads**



1. Electric and Gas Billed Sales and Customer Counts

The following use-per-customer and customer count equations were estimated using historical data from January 1990 to December 2005, depending on sector or class and fuel type. The billed sales forecast is based on the estimated equations, normal weather assumptions, rate forecasts, and forecast of various economic and demographic inputs.

$$\text{UsePerCust}_{c,m} = f(\text{RetailRates}_{c,m}, \text{Weather}_{c,m}, \text{EcoDemo}_{c,m}, \text{MonDummies})$$

$$\text{CustCount}_{c,m} = f(\text{EcoDemo}_{c,m}, \text{MonDummies})$$

$\text{UsePerCust}_{c,m}$ = use (billed sales) per customer for class c, month m

$\text{CustCount}_{c,m}$ = customer counts for class c, month m

RetailRates_{c,m} = effective real retail rates for class c in polynomial distributed lag form of various lengths

Weather_{c,m} = class-appropriate weather variable, cycle-adjusted HDD/CDD using base temperatures of 65, 60, 45, 35 for HDD and 75 for CDD; cycle-adjusted HDDs/CDDs are created to fit consumption period implied by the billing cycles

EcoDemo_{c,m} = class-appropriate economic and demographic variables; variables could be income, household size, population, employment levels or growth, building permits

MonDummies = monthly binary variables

The billed sales forecast for each customer class is the product of use per customer and number of customers for each class, as defined above. Billed sales in a given month are defined as the sum of the billed sales across all customer classes.

BilledSales_{c,m} = UsePerCust_{c,m} × CustCount_{c,m}

Different functional forms were used depending on the customer class. We used a semi-log form for the electric residential use-per-customer equation, with explanatory variables (prices and demographic variables) entering in polynomial distributed lagged form. The length of the lag depends on the customer class equation (residential has the longest lags). We used a double-log form for the other sectors, again with explanatory variables entering in lagged form. Lagged explanatory variables in the equations account for short-term and long-term effects of changes in prices or economic variables on energy consumption. For gas, most of the use-per-customer equations have a linear form with prices or economic variables entering in polynomial distribution lagged form again.

Figure H-2, based on the estimated coefficients for the retail prices in the use-per-customer equations, provides computed long-term price elasticity for the major customer classes for electric and gas.

**Figure H-2
Long-term Price Elasticity for Major Customer Classes**

	Electric	Gas
Residential	-.16	-.11
Commercial	-.18	-.09
Industrial	-.19	-.12

All estimated price coefficients are also statistically significant.

Customer forecasts by county were generated by estimating an equation relating customer counts by class/county to population or employment levels in that county. We imposed a restriction on county-level forecasts so that the sum of forecasted customers across all counties equaled the total service area customer forecast. This projection is an input for the distribution planning process.

The billed sales forecast was further adjusted for discrete additions and deletions not accounted for in the forecast equations. These adjustments include known large additions/deletions or fuel switching, and schedule switching. Finally, total system loads were obtained by distributing monthly billed sales into cycle sales, then allocating the cycle sales into the appropriate calendar months using degree days as weights and adjusting each delivered sales for losses from transmission and distribution. This approach also enables us to compute the unbilled volumes each month.

II. Peak Load Forecasting

A. Electric Peak-hour Load Forecast

For electric, the peak hour for the normal and extreme design temperatures represent the relevant range of peak loads. An hourly regression equation provides "normal" and "extreme" peak loads for both residential and nonresidential sectors. Deviations of actual peak-hour temperature from normal peak temperature for the month, day of the week effects, and unique weather events such as a cold snap are modeled by the equation. We used monthly data from January 1991 to February 2004. The historical data includes a period when large industrial customers opted to leave firm customer classes to join the transportation-only rate class; the equation accounts for this change. Finally, we allow

the impact of peak temperature on peak loads to vary by month. This permits different effects of residential and nonresidential loads on peak demand by season, with and without conservation. It also lets us account for the effects of different customer classes on peak loads. The functional form of the electric peak-hour equation is

$$\begin{aligned} \text{Peak MW} = & \sum_i a_i * \text{Resid aMW} * \text{MoDum}_i + b * \text{Non-Resid aMW} \\ & + \sum_{i=7,8} c1_i * (\text{Normal Mly Temp-Peak Hr Temp}) * (\text{WeathSensitiv aMW}) * \text{MoDum}_i \\ & + \sum_{i=7,8} c2_i * (\text{Normal Mly Temp-Peak Hr Temp}) * (\text{Coml aMW}) * \text{MoDum}_i \\ & + d * \text{Sched48Dummy} + \sum_i e_i * \text{WkDayDum}_i + f * \text{ColdSnapDummy} \end{aligned}$$

where a, b, c1,c2, d, e, and f are coefficients to be estimated.

Peak MW = monthly system peak-hour load in MW

ResidaMW = residential delivered sales in the month in aMW

Non-ResidaMW = commercial plus industrial delivered sale in the month in aMW

MoDum = monthly dummy

Normal Mly Temp-Peak Hr Temp = deviation of actual peak-hour temperature from monthly normal temperature

WeathSensitiv = residential plus a % of commercial delivered loads

Sched48Dummy = dummy variable for when customers in schedule 48 became transport

WkDayDum = day of the week dummy

ColdSnapDummy = 1 if the minimum temperature the day before peak day is less than 32 degrees

To obtain the normal and extreme peak load forecasts, we factor the appropriate design temperatures into the equation for either condition: 23°F for "normal" peak and 13°F for "extreme" peak in December.

B. Gas Peak-day Load Forecast

Gas peak day is assumed to be a function of weather-sensitive delivered sales, the deviation of actual peak-day average temperature from monthly normal average temperature, and other weather events. The following equation used monthly data from October 1996 to March 2004 to represent peak day firm requirements:

$$\text{Peak DThm} = a*\text{FirmDThm} + b*(\text{Normal Mly Temp-Peak Day AvgTemp})*(\text{Firm DThm}) \\ + c*\text{ElNino} + d*\text{WinterDum} + e*\text{SummerDum} + f*\text{ColdSnapDummy}$$

where a, b, c, d, e, and f are coefficients to be estimated.

Peak DThm = monthly system gas peak day load in decatherms

FirmDThm = monthly delivered loads by firm customers

Normal Mly Temp-Peak Day AvgTemp = deviation of actual peak-day average daily temperature from monthly normal temperature

ElNino = dummy for when ElNino is present during the winter

WinterDum, SummerDum = winter or summer dummy variable to account for seasonal effects

ColdSnapDummy = binary variable for when the peak occurred within a cold snap period lasting more than one day, multiplied by the minimum temperatures for the day

This formula for gas peak-day load accounts for changes in use per customer consistent with use-per-customer changes in the billed sales equation. The other advantage is the ability to account for the effects of conservation on peak loads, and for the contribution of customer classes to peak loads.

The design peak-day requirements for this forecast are based on meeting a 52 heating degree day (13°F average temperature for the day), based on the costs and benefits of meeting a higher or lower design day temperature. In the 2003 Least Cost Plan (LCP), we changed PSE's gas supply peak-day planning standard from 55 heating degree days (HDD), which is equivalent to 10 degrees Fahrenheit or a coldest day on record standard, to 51 HDD, which is equivalent to 14 degrees Fahrenheit or a coldest day in 20 years standard. The Washington Utilities and Transportation Commission (WUTC) responded to the 2003 plan with an acceptance letter directing PSE to "analyze" the benefits and costs of this change and to "defend" the new planning standard in the 2005 LCP.

As discussed in our 2005 LCP, appendix I, PSE completed a detailed, stochastic cost-benefit analysis that considered both the value customers place on reliability of service and the incremental costs of the resources necessary to provide that reliability at various temperatures. This analysis determined that it would be appropriate to increase our planning standard from 51 HDD (14°F) to 52 HDD (13°F). PSE's gas planning standard is based on a detailed cost-benefit analysis that relies on the value our natural gas customers attribute to reliability and covers 98% of historical peak events. As such, it is unique to our customer base, our service territory, and the chosen form of energy. Thus, we use projected delivered loads by class and this design temperature to estimate gas peak-day load.

III. Hourly Electric Demand Profile

Because there is no way to store large amounts of electricity in a practical manner, the minute-by-minute interaction between electricity production and consumption is very important. For this reason, and for purposes of analyzing the effectiveness of different electric generating resources, an hourly profile of PSE electric demand is required.

We use our hourly (8,760 hours) load profile of electric demand for the IRP, our power cost calculation, and for other AURORA analyses. This hourly profile replaces a demand profile developed in 2002 with HELM (Hourly Electric Load Model). The new distribution uses actual observed temperatures, recent load data, the latest customer counts, and improved statistical modeling.

A. Data

We developed a representative distribution of hourly temperatures from January 1, 1950 to December 31, 2003. Actual hourly delivered electric loads between January 1, 1994 and December 16, 2004 were used to develop the statistical relationship between temperatures and loads for estimating hourly electric demand based on a representative distribution of hourly temperatures.

B. Methodology for Distribution of Hourly Temperatures

The above temperature data were sorted and ranked to provide two separate data sets:

- For each year, a ranking of hourly temperatures by month, coldest to warmest, over 54 years was used to calculate average monthly temperature.
- A ranking of the times when these temperatures occurred by month, coldest to warmest; these rankings were averaged to provide an expected time of occurrence.

Next we found the hours most likely to have the coldest temperatures (based on observed averages of coldest-to-warmest hour times) and matched them with average coldest-to-warmest temperatures by month. Sorting this information into a traditional time series then provides a representative hourly profile of temperature.

C. Methodology for Hourly Distribution of Load

For the time period January 1, 1994 to December 31, 2003, we used the statistical regression equation

$$\text{Load}_h = \alpha_w + \beta_1 * \text{Load}_{h-1} + \beta_2 * (\text{Load}_{h-2} + \text{Load}_{h-3} + \text{Load}_{h-4})/3 + \beta_3 * \text{Month}_m * \text{temp}_h + \beta_4 * \text{Month}_m * (\text{temp}_h)^2 + \beta_5 * \text{Holiday} + \beta_6 * \text{Linear Trend} + \text{AR}(1)$$

w = 1 to 7 (weekday)

h = 1 to 24 (hours)

m = 1 to 12 (months)

Holiday = NERC holidays

to calculate load shape from the representative hourly temperature profile. The calendar variables for the load profile were derived to follow that of 2005.