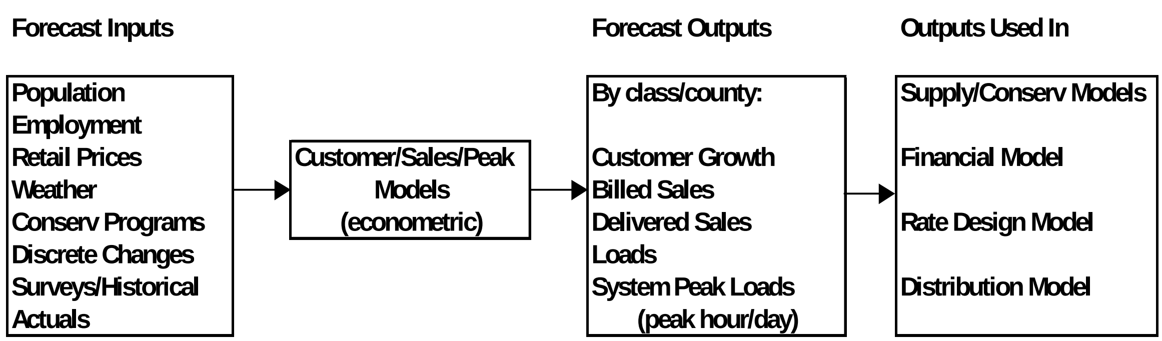
APPENDIX K

DESCRIPTION OF THE LOAD FORECASTING MODELS

This appendix provides a more detailed technical description of the three econometric methodologies used to forecast a) billed energy sales and customer counts, b) system peak loads for electric and gas and c) hourly distribution of loads. The econometric approaches for billed sales, customer counts and peak loads for electric and gas are presented in section 1, while the hourly distribution of loads approach is presented in section 2.

Section 1: Billed Sales, Customer Count and Peak Load Forecast Methodologies

Exhibit K-1
PSE ECONOMETRIC FORECASTING MODEL



For the 2005 LCP, PSE made two types of enhancements to the model over the 2003 LCP version. The enhancements improved the equation formulation or estimation method, and added capabilities to the model. Following is a summary of these enhancements:

- Distinguished electric temperature sensitivity by season, revised all equations
- Improved peak hour/day equations for electric and gas, respectively
- Revised definition of normal weather from average of 30-year hourly temperatures to average of 30-year daily heating or cooling degree days
- Converted “electric billed” to “delivered sales by class” in order to account for unbilled
- Geographically allocated sales/customers into counties
- Accounted for forecast risks/uncertainties using scenarios for sales and Monte Carlo simulations of peaks for weather risks

The first three bullets are enhancements to the equation formulation and estimation method, which improved the accuracy and relevance of the forecast outputs, while the last three bullets are added capabilities to the model to enable PSE to produce delivered sales forecasts for peak load forecasting and to determine where load growth is occurring in the service territory.

Equations for Electric or Gas Billed Sales

The following use-per-customer and customer equations were estimated using historical data from January 1990 to December 2003, depending on the sector and fuel type. The forecast of billed sales uses the estimated equations, normal weather assumptions together with the forecasts of rates, and various economic and demographic inputs.

$$\mathbf{UsePerCust_{c,m} = f(RetailRates_{c,m}, Weather_{c,m}, EcoDemo_{c,m}, MonDummies)}$$

$$\mathbf{CustCount_{c,m} = f(EcoDemo_{c,m}, MonDummies)}$$

where $\mathbf{UsePerCust_{c,m}}$ = use (billed sales) per customer for class c, month m

$\mathbf{CustCount_{c,m}}$ = customer counts for class c, month m

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

$\mathbf{Weather_{c,m}}$ = class appropriate weather variable, cycle adjusted HDD/CDD using base temps 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

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

MonDummies = monthly binary variables

Given the forecast of use per customer and customer counts above, the billed sales forecast for each customer class is the product of two components: use per customer and number of customers for each class, as shown below.

$$\mathbf{BilledSales_{c,m}} = \mathbf{UsePerCust_{c,m} \times CustCount_{c,m}}$$

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

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

Exhibit K-2
Long-Term Price Elasticity for Major Customer Classes

	Electric	**Gas**
Residential	-.19	-.09
Commercial	-.16	-.08
Industrial	-.19	-.10

All of the estimated price coefficients are also statistically significant.

Electric customer forecasts by county were also generated by estimating an equation relating customer counts by class/county, and population or employment levels in that county. In producing the county level forecasts, a restriction was imposed so that the sum of forecasted customers across all counties equaled the total service area customer counts forecast. This projection is an input into 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 the company's forecast of new programmatic conservation savings for each customer class, 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 PSE to compute the unbilled volumes each month

Electric Peak-Hour Load Forecast

PSE uses an hourly regression equation to obtain monthly peak load forecasts. This equation provides "normal" and "extreme" peak loads for both residential and non-residential 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 all variable conditions modeled by the equation. PSE estimated the equation using 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 also accounts for this change in historical series. Finally, PSE allows the impact of peak temperature on peak loads to vary by month. This specification allows for different effects of residential and non-residential loads on peak demand by season, with and without conservation. It also allows PSE to account for the effects of different customer classes on peak loads. The functional form of the electric peak-hour equation is displayed below:

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

where a, b, c1,c2, d, e, 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
Normal Mly Temp-Peak Hr Temp = deviation of actual peak-hour temp from monthly normal temp
WeathSensitv = residential plus a % of commercial delivered loads
Sched48Dummy = dummy variable for when customers in schedule 48 became transport
WkDayDum = day of the week dummy
MoDum = monthly dummy

ColdSnapDummy = 1 if the min temp the day before peak day is less than 32 degrees

These equations are estimated to account for truncation or censoring effects due to some customers being out of service during cold events. To obtain the normal and extreme peak load forecasts, PSE factors the appropriate design temperatures into the equation for either condition. For PSE, these design temperatures are 23 degrees for "normal" peak and 13 degrees for "extreme" peak. Peak hourly loads are also produced for 16 degrees Fahrenheit.

Gas Peak-Day Load Forecast

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

Peak DThm = a*FirmDThm + b*(Normal Mly Temp-Peak Day AvgTemp)*(Firm DThm)

+ c*ElNino + d*WinterDum + e*SummerDum + f*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 aver daily temp from monthly normal temp
ElNino = dummy for when ElNino is present during the winter
ColdSnapDummy = binary variable for when the peak occurred within a cold snap period lasting more than one day, multiplied by the minimum temps for the day
WinterDum, SummerDum = winter or summer dummy variable to account for seasonal effects

This formulation for gas peak-day load accounts for changes in use per customer consistent with those use-per-customer changes in the billed sales equation. This feature was not available in the last Least Cost Plan because the base and weather sensitive use per customer in that equation were not a function of the key demand drivers such as economic inputs, retail rate inputs and conservation. The other advantage of this formulation is the ability to account for the effects of conservation on peak loads, and for the contribution of customer classes to peak loads. The estimation method further accounts for truncation biases to recognize that some firm customers may have been out of service during some cold events.

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 analysis of the costs and benefits of meeting a higher or lower design day temperature. Thus, using the projected delivered loads by class and this design temperature, a forecast of gas peak day load can be estimated.

Section 2: Creation of an Hourly Electricity Demand Profile

PSE updated its hourly (8760 hours) load profile of electricity demand to be used for the Least Cost Plan, Power Cost calculation, and other AURORA analysis. This hourly profile replaces a previous electricity demand profile developed in 2002 with use of the hourly electricity demand modeling program: HELM (Hourly Electric Load Model). The new distribution makes use of actual observed temperatures, recent load data, the latest customer counts, and improved statistical modeling.

Data: Hourly observed temperatures from 1/1/1950 to 12/31/2003 were used to develop a representative distribution of hourly temperatures. PSE's actual hourly delivered electricity loads from 1/1/1994 to 12/16/2004 were used to develop the statistical relationship between temperatures and loads for use in estimating the hourly electricity demand based on the representative distribution of hourly temperatures.

Methodology for distribution of hourly temperatures

The above described temperature data was sorted and ranked to provide two separate data sets: 1) For each year, a ranking of the hourly temperatures by month: coldest to warmest. The average for 54 years' worth of monthly temperature data, ranked coldest to warmest, is calculated. 2) A ranking of the times when the temperatures occurred by month: coldest to warmest. These hourly time rankings were averaged to provide an expected time of occurrence.

The next step was to find the hours most likely to have the coldest temperatures (based on the observed averages of the rankings of coldest to warmest hour times) and match them up with the average coldest to warmest temperatures, by month. Sorting this information into a traditional time series then gives us the representative hourly profile of temperature.

Methodology for hourly distribution of load

For the time period 1/1/1994 to 12/31/2003, the following statistical regression equation was developed:

$Load_h = \alpha_w + \beta_1 * Load_{h-1} + \beta_2 * (Load_{h-2} + Load_{h-3} + Load_{h-4})/3 + \beta_3 * Month_m * temp_h$
$+ \beta_4 * Month_m * (temp_h)^2 + \beta_5 * Holiday + \beta_6 * Linear\ Trend + AR(1)$

w = 1 to 7 (weekday)
h = 1 to 24 (hours)
m = 1 to 12 (months)
Holiday = NERC holidays

Using this regression equation, the load shape can be developed from the representative hourly temperature profile. The calendar variables for the load profile are derived to follow that of calendar year 2005.