DEMAND FORECAST ANALYSIS

APPENDIX D

PUGET SOUND ENERGY

Contents

1. Demand Forecast Methodology

Puget Sound Energy (PSE) employed time-series econometric methods to forecast monthly energy demand and peaks for PSE's gas utility service area. We gathered sales, customer, demand, weather, economic, and demographic variables to model use per customer (UPC), customer counts, and peaks. Once we completed the modeling, we used internal and external forecasts of new major demand (block sales), retail rates, economic and demographic drivers, normal weather with climate change assumptions, and demand side resources (DSR) to create a 27-year projection of monthly demand and peaks. For Puget Sound Energy's 2023 Gas Utility Integrated Resource Plan (2023 Gas Utility IRP), block sales refer to large demand entities entering the system, leaving the system, or dramatically changing their demand in a way we would not otherwise capture in the modeling. The IRP's base demand forecast for energy and peaks reflects DSR, including committed short-term conservation program targets and short-term codes and standards. Figure D.1 depicts the demand forecast development process.

Figure D.1: Demand Forecast Development Process

Estimate Models: Use per Customer, Customer Counts, Peak

- Billed sales volume and system loads
- Customer counts
- Economic and demographic observations
- Effective retail rates
- Weather observations at Sea-Tac Airport station

Forecast Models: Use per Customer, Customer Counts, Peak

- Economic and demographic forecasts
- Normal weather using historic and forecasts temperatures
- Retail rate forecast

Base Demand Forecasts, before additional DSR: Demand and Peak

- 2022-2023 effects of DSR, including programmatic conservation and code and standards
- Billing cycles schedules
- Losses
- Major projects including system additions and departures, CNG forecast

Final Demand Forecast, after additional DSR: Demand and Peak

- 2023 Gas Utility IRP Demand Side Resources 2024–2050
- Effects of 70% more efficient building codes
- Effects of the Climate Commitment Act
- Impacts of electrification

2. Model Estimation

To capture incremental customer growth, temperature sensitivities, and economic sensitivities, we forecasted billed sales by estimating UPC and customer count models. We created models for the following major classes to best estimate each class's specific driving forces.

- Firm classes — residential, commercial, industrial, commercial large volume, and industrial large volume
- Interruptible classes — commercial and industrial
- Transport classes — commercial firm, commercial interruptible, industrial firm, and industrial interruptible

Each class's historical sample period ranged from as early as January 2003 to March 2021.

➔ See Chapter Five: Demand Forecasts for how we developed the economic and demographic input variables.

2.1. Customer Counts

We estimated monthly customer counts by class. These models use explanatory variables such as population, total employment, and manufacturing employment. We estimated some customer classes via first differences, with economic and demographic variables implemented in a lagged or polynomial distributed form to allow delayed variable impacts. We did not estimate some smaller customer classes but instead held them constant. We also imposed autoregressive moving average (ARMA) (p,q) error structures subject to model fit.

The equation we used to estimate customer counts is:

$$\mathrm{CC}_{\mathrm{C,t}} = \boldsymbol{\beta}_{\mathbf{C}}[\propto_{\mathrm{C}} \quad \mathbf{D}_{\mathrm{M,t}} \quad \mathrm{T}_{\mathrm{C,t}} \quad \mathbf{ED}_{\mathrm{C,t}}] + \mathrm{u}_{\mathrm{C,t}},$$

The details for the estimating equation components are as follows:*

$CC_{C,t}$	=	Count of customers in Class C and month t
C	=	Service and class, as determined by tariff rate
t	=	Estimation period
$\boldsymbol{\beta_C}$	=	Vector of CC_C regression coefficients estimated using Conditional Least Squares/ARMA methods
$\propto_C$	=	Indicator variable for class constant (if applicable)
$\boldsymbol{D}_{M,t}$	=	Vector of month/date-specific indicator variables
$T_{C,t}$	=	Trend variable (not included in most classes)
$\boldsymbol{ED}_{C,t}$	=	Vector of economic and/or demographic variables

$u_{C,t}$ = ARMA error term (ARMA terms chosen in model selection process)

Note: The term vector or boldface type denotes one or more variables in the matrix.

2.2. Use Per Customer

We estimated monthly UPC at the class level using explanatory variables, including heating degree days (HDD), seasonal effects, retail rates, average billing cycle length, and various economic and demographic variables such as income and employment levels. We modeled some variables, such as retail rates and economic variables, in a lagged form to account for short-term and long-term effects on energy consumption. Finally, depending on the equation, we employed an ARMA(p,q) error structure to address issues of autocorrelation.

The equation we used to estimate use per customer is:

$$\frac{UPC_{C,t}}{D_{c,t}} = \boldsymbol{\beta_C}\left[\propto_C \quad \frac{\boldsymbol{DD}_{C,t}}{D_{C,t}} \quad \boldsymbol{D}_{M,t} \quad \boldsymbol{RR}_{C,t} \quad \boldsymbol{ED}_{C,t}\right] + u_{C,t}$$

$UPC_{C,t}$ = Billed Sales ($Billed\ Sales_{C,t}$) divided by Customer Count ($CC_{C,t}$), in class C, month t

$D_{C,t}$ = Average number of billed cycle days for billing month t in class C

$\boldsymbol{\beta_C}$ = Vector of UPC_C regression coefficients estimated using Conditional Least Squares/ARMA methods

$\propto_C$ = Indicator variable for class constant (if applicable)

$\boldsymbol{DD}_{C,t}$ = Vector of weather variables, a calculated value that drives monthly heating and/or cooling demand.

$$\boldsymbol{HDD}_{C,Base,t} = \sum_{d=1}^{Cycle_t} |max(0, Base\ Temp - Daily\ Avg\ Temp_d)| * BillingCycleWeight_{C,d,t}$$

$\boldsymbol{D}_{M,t}$ = Vector of month/date-specific indicator variables

$\boldsymbol{RR}_{C,t}$ = The effective retail rate. The rate is smoothed, deflated by a Consumer Price Index, and interacts with macroeconomic variables, and/or is further transformed.

$\boldsymbol{ED}_{C,t}$ = Vector of economic and/or demographic variables

$u_{C,t}$ = ARMA error term

The term vector or boldface type denotes one or more variables in the matrix.

2.3. Gas Utility Peak Day

The gas peak demand model relates observed monthly peak system demand to monthly weather-normalized delivered demand. The model also controls for other factors, such as observed temperature, exceptional weather events, and the day of the week.

The primary driver of a peak demand event is temperature. In winter, colder temperatures yield higher demand during peak hours, especially on evenings and weekdays. The peak demand model uses the difference of observed peak temperatures from normal monthly peak temperature and month-specific variables, scaled by normalized average monthly delivered demand, to model the weather and non-weather sensitive components of monthly peak demand. In the long-term forecast, growth in monthly weather-normalized delivered demand will drive growth in forecasted peak demand, given the relationships established by the estimated regression coefficients.

The equation we used to estimate the gas utility peak day is:

$$\max\left(Day_{1,t} \ldots Day_{Days_{t},t}\right) = \boldsymbol{\beta}\left[BDemand_{N,t} \quad \Delta Temperature_{N,t} HDemand_{N,t} \quad \boldsymbol{D}_{M,t} \quad \boldsymbol{D}_{WE,t} \quad \boldsymbol{S}_{i,t}\right] + \varepsilon_t$$

$Day_{i,t}$	=	Firm delivered dekatherms for day i
$Days_t,$	=	Total number of days in a month at time t
$\boldsymbol{\beta}$	=	Vector of gas peak day regression coefficients
$HDemand_{N,t}$	=	Normalized monthly firm-delivered heating demand
$BDemand_{N,t}$	=	Normalized monthly firm-delivered base load demand
$\Delta\, Temperature_{N,t}$	=	Deviation of observed daily average temperature from the normal minimum temperature for that month
$\boldsymbol{D}_{M,t}$	=	Vector of monthly date indicator variables
$\boldsymbol{D}_{WE,t}$	=	Vector of date-specific indicator variables
$\mathbf{S}_{i,t}$	=	Vector of snow day binaries
ε_t	=	Error term

The gas utility peak day equation uses monthly normalized firm-delivered demand as an explanatory variable; the estimated model weighs this variable heavily. Therefore, the peak day equation will follow a similar trend as the monthly firm demand forecast with minor deviations based on the impact of other explanatory variables. An advantage of this process is that it uses the demand of distinct gas customer classes to help estimate gas peak demand.

2.4. Billed Sales Forecast

PSE used the described UPC and customer count models and external and internally derived forecast drivers to forecast billed sales. We fitted economic, demographic, and retail rate forecasts, and normal monthly degree days, including climate change with model estimates to create the 27-year UPC and customer count projections by class. We formed the total billed sales forecasts by class by multiplying forecasted UPC and customers ($\widehat{UPC}_{C,t} * D_{C,t} * \widehat{CC}_{C,t}$), then adjusting for known future discrete additions and subtractions ($Block\ Sales_{C,t}$).

We incorporated major block sales changes as additions or departures to the sales forecast as they are not reflected in historical trends in the estimation sample period. Examples of such items include large greenfield developments, changes in usage patterns by large customers, schedule switching by large customers, and fuel switching by customers. Finally, for the 2023 Gas Utility IRP base demand forecast, we reduced the forecast of billed sales by DSR. DSR ($DSR_{C,t}$) includes new conservation programs by class, using established conservation targets in 2022–2023 and short-term effects of codes and standards for 2022–2023.

The total billed sales forecast equation by class and service is:

$$Billed\ Sales_{C,t} = \widehat{UPC}_{C,t} * D_{C,t} * \widehat{CC}_{C,t} + Block\ Sales_{C,t} - DSR_{C,t}$$

t	=	Forecast time horizon
$\widehat{UPC}_{C,t}$	=	Forecast use per customer
$D_{C,t}$	=	Average number of scheduled billed cycle days for billing month t in class C
$\widehat{CC}_{C,t}$	=	Forecast count of customers
$DSR_{C,t}$	=	Base Forecast: programmatic conservation targets and codes and standards for 2022 and 2023
$Block\ Sales_{C,t}$	=	Expected entering or exiting sales not captured as part of the customer count or UPC forecast.

We calculated total billed sales each month as the sum of the billed sales across all customer classes.

$$\text{Total}\ Billed\ Sales_t = \sum_c Billed\ Sales_{C,t}$$

2.5. Base and Final Demand Net of DSR Forecasts

To calculate the final demand, we applied the DSR from this IRP to the base demand forecast. We used this process for the energy demand and peak demand.

2.5.1. Energy Demand

We formed total system demand by distributing monthly billed sales into calendar sales, then made minor adjustments for company own use and losses from distribution. The gas demand forecast ($\widehat{Demand}_{N,t}$) forms the 2023 Gas Utility IRP gas utility base demand forecast. We calculated final demand using the optimal DSR bundles found in this IRP.

2.5.2. Peak Demand

We used the peak models, the assumption of normal design temperature, forecasted total system normal demand less DSR ($\widehat{Demand}_t - DSR_t$), and short-term forecasted peak DSR targets to forecast peak demand. Peak DSR and demand DSR are related but distinct: different conservation measures may have more significant or minor impacts on peak when compared with energy. Thus, the peak model reflects exact peak DSR assumptions from program activities and codes and standards, as opposed to simple downstream calculations from demand reduction. These calculations yield system daily peak demand for each winter month based on normal design temperatures.

$$Peak\ Demand_t = F(\widehat{Demand}_{t,}, \Delta Temperature_{N,Design,t}) - DSR_{Peak,t}$$

$Peak\ Demand_t$	=	Forecasted maximum system demand for month t
t	=	Forecast time horizon
$\widehat{Demand}_t$	=	Forecast of delivered demand for month t
$\Delta Temperature_{Normal,Design,t}$	=	Deviation of peak hour/day design temperature from monthly normal peak temperature
$DSR_{Peak,t}$	=	Peak DSR resulting from programmatic conservation targets and codes and standards from the previous conservation potential assessment (CPA)

For the gas peak day forecast, the design peak day is a 52-heating-degree day (13 degrees Fahrenheit average temperature for the day). We evaluated this standard when we adopted climate change models for future weather.

➔ See the Climate Change Forecasts section of this Appendix for the analysis.

We netted the effects of the 2022 and 2023 DSR targets from the peak demand forecast to account for programmatic conservation already underway for the 2023 Gas Utility IRP base peak demand forecast. Additionally, we netted the effects of codes and standards in 2022 and 2023 and created the base peak demand forecast. Once we determined the optimal DSR for this IRP, we adjusted the peak demand forecast for the peak contribution of future DSR, creating the final demand peak forecast.

2.6. Details of the Natural Gas Forecast

The natural gas forecast is comprised of demand from several different classes. The firm classes are residential, commercial, industrial, commercial large volume, and industrial large volume. The interruptible classes are commercial and industrial. Transport classes are commercial firm, commercial interruptible, industrial firm, and industrial interruptible. We show details of each class in the following section.

2.6.1. Natural Gas Customer Counts

The base demand forecast projects the number of natural gas customers will increase at a rate of 0.9 percent per year on average between 2024 and 2050, reaching 1.133 million customers by the end of the forecast period for the system. Overall, customer growth is slower than the 1.0 percent average annual growth rate projected in the 2021 IRP for 2022–2041.

Residential customer counts drive the growth in total customers since this class makes up, on average, 94 percent of PSE's natural gas sales customers. We expect the number of residential customers to grow at an average annual rate of 0.9 percent from 2024 to 2050. The next largest group, commercial customers, is expected to grow at an average annual rate of 0.2 percent over the same time. We expect industrial and interruptible customer classes to continue to shrink, consistent with historical trends.

Table D.1: December Natural Gas Customer Counts by Class, 2023 Gas Utility IRP Base Demand Forecast

Customer Type	2024	2030	2035	2040	2045	2050	AARG 2024–2050
Residential	837,050	892,262	938,133	982,658	1,027,267	1,070,074	0.9%
Commercial	58,015	59,013	59,764	60,285	60,748	60,896	0.2%
Industrial	2,213	2,110	2,024	1,938	1,852	1,766	-0.9%
Total Firm	897,278	953,385	999,921	1,044,881	1,089,867	1,132,736	0.9%
Interruptible	124	88	58	28	9	9	-9.1%
Total Firm & Interruptible	897,402	953,473	999,979	1,044,909	1,089,876	1,132,745	0.9%
Transport	220	220	220	220	220	220	0.0%

Customer Type	2024	2030	2035	2040	2045	2050	AARG 2024–2050
System Total	897,622	953,693	1,000,199	1,045,129	1,090,096	1,132,965	0.9%

2.6.2. Natural Gas Use per Customer

Table D.2 below shows all firm use per customer at the meter.[3] Residential use per customer before DSR is declining, showing a -0.4 percent average annual growth for the forecast period. We expect commercial use per customer to rise slowly at 0.3 percent annually over the forecast horizon due to assumptions about increases in employment. Industrial use per customer has been declining in recent years, and we expect it will continue to decline at -0.4 percent average annual growth. The commercial and industrial classes do not include interruptible or transport class usage. These classes can have different-sized customers, and very large customers can skew the use per customer value.

Table D.2: Natural Gas Use per Customer before Additional DSR,
2023 IRP Gas Base Demand Forecast (therms[4]/customer)

Customer	2024	2030	2035	2040	2045	2050	AARG 2024–2050
Residential	713	689	675	667	651	644	-0.4%
Commercial	4,919	5,002	5,089	5,184	5,223	5,296	0.3%
Industrial	9,474	9,132	8,978	8,859	8,651	8,543	-0.4%

2.6.3. Natural Gas Demand by Class

We expect total energy demand, including transport, to increase at an average rate of 0.5 percent annually between 2024 and 2050. Residential demand, which we forecast to represent 50 percent of demand in 2024, is expected to increase on average by 0.6 percent annually during the forecast period. Commercial demand, which we forecast to represent 24 percent of demand in 2024, is expected to increase by 0.4 percent on average.

Population growth is driving residential demand growth. Commercial demand growth is driven by increases in customer counts and use per customer. We expect demand in the industrial and interruptible sectors to decline as manufacturing employment in the Puget Sound area continues to slow. We expect demand from the transport class to grow by 0.9 percent annually over the forecast period, mainly due to the increase in usage by a small number of customers.

Table D.3: Natural Gas Energy Demand by Class Base Demand Forecast before Additional DSR (MDth)

Class	2024	2030	2035	2040	2045	2050	AARG 2024-2050
Residential	59,284	61,084	62,951	65,172	66,495	68,610	0.6%
Commercial	28,783	29,695	30,527	31,275	31,705	32,239	0.4%
Industrial	2,129	1,959	1,850	1,749	1,634	1,541	-1.2%
Total Firm	90,196	92,739	95,328	98,196	99,834	102,390	0.5%
Interruptible	2,873	2,099	1,458	794	259	258	-8.4%
Total Firm and Interruptible	93,069	94,838	96,786	98,989	100,093	102,648	0.4%
Transport	24,183	27,741	28,219	28,771	29,375	30,226	0.9%
System Total before Losses	117,252	122,579	125,005	127,760	129,468	132,873	0.5%
Losses	1,101	1,151	1,173	1,199	1,215	1,247	-
System Total	118,353	123,730	126,179	128,959	130,684	134,121	0.5%

2.6.4. Natural Gas Customer Count and Energy Demand Share by Class

We show customer counts as a percent of PSE's total natural gas customers in Table D.4 and demand share by class in Table D.5.

Table D.4: Natural Gas Customer Count Share by Class Base Demand Forecast

Class	Share in 2024	Share in 2050
Residential	93.3%	94.4%
Commercial	6.5%	5.4%
Industrial	0.2%	0.2%
Interruptible	0.01%	0.001%
Transport	0.02%	0.02%

Table D.5: Natural Gas Demand Share by Class Base Demand Forecast before Additional DSR

Class	Share in 2024	Share in 2050
Residential	50.1%	51.2%

Class	Share in 2024	Share in 2050
Commercial	24.3%	24.0%
Industrial	1.8%	1.1%
Interruptible	2.4%	0.2%
Transport	20.4%	22.5%
Losses	0.93%	0.93%

3. Climate Change Assumptions

This IRP is the first time PSE incorporated climate change temperatures into the forecast of energy demand and peak demand. This section describes in detail how we calculated future temperature assumptions.

3.1. Energy Forecast Temperatures

Puget Sound Energy's demand forecasting models employ various thresholds of heating degree days, consistent with industry practices. Monthly heating degree days help estimate the weather-sensitive demand in the service area. Most of PSE's customer classes are weather sensitive, so our model assumed normal degree days for these classes. A heating degree day measures the heating severity, defined by the distance between a base temperature and the average daily temperature. The UPC models we discussed use historical observations to derive UPC to heating degree day sensitivities, which we then forecasted forward with the normal assumption. Previously, PSE defined normal degree days as the monthly average of 30 years before the forecast was created. For example, the 2021 IRP normal definition spanned 1990–2019. For the 2023 Gas Utility IRP, we defined normal degree days as a rolling weighted average of the 15 years prior to the forecast year and 15 years after, including the forecast year. Values for the years after historical actuals are three climate change models provided by the Northwest Power and Conservation Council (NWPCC). The new definition results in warmer winters, thereby decreasing total heating demand. The net effect of these assumptions for every year in the forecast is negative. What follows is how we calculated future degree days.

We defined Heating Degree Days $\boldsymbol{HDD_{M,Base,t}}$ for a scenario (M), base temperature, and observation time (t) as:

$$\mathbf{HDD}_{\mathrm{M,Base,t}} = \sum_{\mathrm{d}=1}^{\mathrm{Days_t}} \max\left(0, \mathrm{Base\ Temp_t} - \mathrm{Daily\ Avg\ Temp_{d,M}}\right)$$

To calculate normal heating degree days, we collected historical actual degree days and weighted averages of the future degree day model for a period using the following data set:

$$\mathbf{HDD}_{\mathrm{Base},t} = \begin{cases} \mathbf{HDD}_{\mathrm{Actuals4,Base},t} \text{ for } t < \text{Jan 2021} \\ \frac{\mathbf{1}}{\mathbf{3}}\left(\mathbf{HDD}_{\mathrm{CanESM2,Base},t} + \mathbf{HDD}_{\mathrm{CCSM4,Base},t} + \mathbf{HDD}_{\mathrm{CNRM-CM5_{MACA},Base},t}\right) \text{for } t > \text{Dec 2020} \end{cases}$$

To calculate normal degree days, $\boldsymbol{DDN_T}$, we calculated the average of monthly degree days for the 15 years prior and 15 years forward, using actual temperature data or the weighted average of the models.

$$\mathbf{DDN}_{\mathrm{T}} = \frac{\mathbf{1}}{\mathbf{30}} \sum_{t=T-15}^{T+14} \mathbf{HDD}_{\mathrm{Base},t} \text{ , T = Jan 2024 – Dec 2050}$$

3.2. Design Temperature for Peak Forecast

The gas design peak in the 2021 IRP was a 52-heating-degree day (13 degrees Fahrenheit average temperature for the day). This gas utility planning standard was based on the coldest annual daily temperature from 1950–2019 and was the 1-in-50, or 98th percentile, of historic peak events.

The new gas design peak is also a 52-heating-degree day (13 degrees Fahrenheit average temperature for the day). The new design peak temperature uses historic data from 2010-2019 and climate data from three climate models for the years 2020 to 2049. This gas planning standard is still based on 1-in-50, or 98th percentile, the coldest annual daily temperature during that time. See Table D.6 for a comparison of the years used and the number of observations used in each calculation.

Table D.6: Comparison of Previous and Current Gas Utility Design Peak Temperature Calculations

Data Set	Years Used	Number of Observations	1-in-50 Daily Temperature (ºF)
Previous IRP	1950–2019	79	13
Current 2023 Gas Utility IRP (Includes Climate Change)	2010–2049	98	13

4. Stochastic Demand Forecasts

Demand forecasts are inherently uncertain, and to acknowledge this uncertainty, the 2023 Gas Utility IRP considers stochastic forecast scenarios. Examples of drivers of forecast uncertainty include future temperatures, customer growth, and usage levels. We created 250 stochastic monthly demand and peak forecasts to model these uncertainties for different IRP analyses.

Stochastic models estimate the probability of various outcomes while allowing for randomness in one or more inputs over time.

4.1. Monthly Demand and Peak Demand

The demand forecasts assumed economic, demographic, temperature, and model uncertainty to create the set of stochastic demand forecasts.

4.1.1. Economic and Demographic Assumptions

The econometric demand forecast equations depend on specific economic and demographic variables; these vary depending on whether the equation is for customer counts or UPC and whether the equation is for a residential or non-residential customer class. In PSE's demand forecast models, the key service area economic and demographic inputs are population, employment, consumer price index (CPI), and manufacturing employment. These variables are inputs into one or more demand forecast equations.

We performed a stochastic simulation of PSE's economic and demographic model to produce the distribution of PSE's economic and demographic forecast variables to develop the stochastic demand simulations. Since these variables are a function of key U.S. macroeconomic variables such as population, employment, unemployment rate, personal income, personal consumption expenditure index, and long-term mortgage rates, we utilized the stochastic simulation functions in EViews[1] by providing the standard errors for the quarterly growth of key U.S. macroeconomic inputs into PSE's economic and demographic models. These standard errors were based on historical actuals from the last 30 years, ending in 2021. This created 1,000 stochastic simulation draws of PSE's economic and demographic models, which provided the basis for developing the distribution of the relevant economic and demographic inputs for the demand forecast models over the forecast period. We removed unrealistic outliers from the 1,000 economic and demographic draws. We then ran 250 draws through the gas utility demand forecast to create the 250 stochastic simulations of PSE's demand forecast.

4.1.2. Temperature

We modeled uncertainty in the levels of the heating load by varying future years' degree days and temperatures. We randomly assigned annual normal weather scenarios from three climate models (CanESM2_BCSD, CCSM4_BCSD, and CNRM-CM5_MACA). We used weather data from these climate models from 2020 to 2049 in the stochastic simulations.

4.1.3. Model Uncertainty

The stochastic demand forecasts consider model uncertainty by adjusting customer growth and usage by normal random errors, consistent with the statistical properties of each class regression model. These model adjustments are consistent with Monte-Carlo methods of assessing regression models' uncertainty.

[1] EViews is a popular econometric forecasting and simulation tool.