DEMAND FORECAST
APPENDIX F

PUGET SOUND ENERGY

2023 Electric Progress Report

Contents

1. Introduction

We employed time series econometric methods to forecast monthly energy demand and peaks for Puget Sound Energy's (PSE) electric 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, and short-term demand-side resource (DSR) forecasts to create a long-term projection of monthly demand and peaks. Puget Sound Energy's 2023 Electric Progress Report (2023 Electric Report) base demand forecast for energy reflects short-term DSR via codes and standards impacts, and committed energy efficiency program targets through 2023. The 2023 Electric Report base demand net of DSR also reflects the optimal DSR we chose in the 2023 report analysis. Figure F.1 depicts the demand forecast development process.

Figure F.1: Demand Forecast Development Process

Model Estimation: Billed Sales, Customer Counts, Peak

- Billed sales volume, Effective Retail Rates
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2. Model Estimation

To capture incremental customer growth, temperature sensitivities, and economic sensitivities, we forecasted billed sales by estimating UPC and customer count models. Models are disaggregated into the following major classes and sub-classes, or sectors as determined by tariff rate schedule, to best estimate the underlying determinants of each class.

- Commercial — high-voltage interruptible, large, small/medium, lighting
- Industrial — high-voltage interruptible, large, small/medium
- Resale
- Residential
- Streetlights

Each class's historical sample period ranged from January 2003 to December 2021. Some class estimation periods start later than January 2003 or end earlier than December 2021 to isolate the impacts of the COVID-19 pandemic without impacting the long-term forecast levels and sensitivities.

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

2.1. Customer Counts

We estimated monthly customer counts by class and sub-class. These models use explanatory variables such as population, unemployment rate, and total and sector-specific employment. We estimated larger customer classes via first differences, with economic and demographic variables implemented in a lagged or polynomial distributed lag form to allow delayed variable impacts. Some smaller customer classes are held constant. The team also utilized autoregressive moving average (ARMA) (p,q) error structures, subject to model fit.

The equation we used to estimate customer counts is[1]:

$$CC_{C,t} = \boldsymbol{\beta_C}[\propto_C \quad \boldsymbol{D}_{M,t} \quad T_{C,t} \quad \boldsymbol{ED}_{C,t}] + u_{C,t},$$

The details for the estimating equation components are:

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

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

2.2. Use Per Customer

We estimated monthly use per customer (UPC) at the class and sub-class levels using multiple explanatory variables. Major drivers include heating degree days (HDD), cooling degree days (CDDs), seasonal effects, retail rates, and average billing cycle length. We also used economic and demographic variables such as income and employment levels. Finally, an ARMA(p,q) is added depending on the equation. The equation we used to estimate UPC is[2]:

$$\frac{UPC_{C,t}}{D_{c,t}} = \boldsymbol{\beta_C}\left[\propto_C \quad \frac{\boldsymbol{DD_{C,t}}}{D_{C,t}} \quad \boldsymbol{D_{M,t}} \quad T_{C,t} \quad \boldsymbol{RR_{C,t}} \quad \boldsymbol{ED_{C,t}}\right] + u_{C,t}$$

The details for the estimating equation components are:

$\boldsymbol{UPC_{C,t}}$	=	Billed Sales ($\boldsymbol{Billed\ Sales_{C,t}}$) divided by Customer Count ($\boldsymbol{CC_{C,t}}$)
$\boldsymbol{D_{C,t}}$	=	Average of billed cycle days for billing month t in class C
$\boldsymbol{\beta_C}$	=	Vector of regression coefficients
$\propto_C$	=	Indicator variable for class constant (if applicable)
$\boldsymbol{DD_{C,t}}$	=	Vector of weather variables ($\mathbf{HDD}_{\mathrm{C,Base,t=45}}, \dots, \mathbf{HDD}_{\mathrm{C,Base,t=65}}$ $\mathbf{CDD}_{\mathrm{C,Base,t=55}}, \dots, \mathbf{CDD}_{\mathrm{C,Base,t=70}}$). These are calculated values that drive monthly heating and cooling demand.
$\mathbf{HDD}_{\mathrm{C,Base,t}}$	=	$\sum_{d=1}^{\mathrm{Cycle}_t} \lvert \max(0, \mathrm{Base\ Temp} - \mathrm{Daily\ Avg\ Temp}_d) \rvert$
$\mathbf{CDD}_{\mathrm{C,Base,t}}$	=	$\sum_{d=1}^{\mathrm{Cycle}_t} \lvert \max(0, \mathrm{Daily\ Avg\ Temp}_d - \mathrm{Base\ Temp}) \rvert * \mathrm{BillingCycleWeight}_{\mathrm{C,d,t}}$
$\boldsymbol{D_{M,t}}$	=	Vector of month/date-specific indicator variables
$\boldsymbol{T_{C,t}}$	=	Trend variable (not included in most classes)
$\boldsymbol{RR_{C,t}}$	=	The effective retail rate. The rate is smoothed, deflated by a Consumer Price Index, interacted with macroeconomic variables, and further transformed.
$\boldsymbol{ED_{C,t}}$	=	Vector of economic and/or demographic variables
$\boldsymbol{u_{C,t}}$	=	ARMA error term

2.3. Peak Electric Hour

The electric peak demand model relates observed monthly peak system demand to monthly weather-normalized demand. The model also controls for other factors, such as observed hourly temperature, holidays, the day of the week, and the time of day.

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

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 equation 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. In the long-term forecast, growth in monthly weather-normalized demand will drive growth in forecasted peak demand, given the relationships established by the estimated regression coefficients.

The equation we used to estimate electric peak hourly demand is:

$$\boldsymbol{max}(\boldsymbol{Hour}_{1,t} \ldots \boldsymbol{Hour}_{H_t,t}) =$$

$$\boldsymbol{\beta}\left[\frac{Demand_{N,t}}{H_t}\boldsymbol{D}_{M,t} \quad \Delta Temperature_{N,t}\frac{Demand_{N,t}}{H_t}\boldsymbol{D}_{S,t}\boldsymbol{D}_{PeakType,t} \quad \boldsymbol{D}_{DoW,t} \quad D_{LtHr,t} \quad D_{Hol,t} \quad T_{Hot,t}\right] + \varepsilon_t$$

$\boldsymbol{Hour}_{J,t}$	=	Hourly PSE system demand (MWs) for hour j=1 to H_(t,)
$\boldsymbol{H}_t$	=	Total number of hours in the month at time t
$\boldsymbol{\beta}$	=	Vector of electric peak hour regression coefficients
$\boldsymbol{Demand}_{N,t}$	=	Normalized total demand in a month at time t
$\Delta\boldsymbol{Temperature}_N$	=	Deviation of actual peak hour temperature from the hourly normal minimum peak temperature
$\boldsymbol{D}_{M,t}$	=	Vector of monthly date indicator variables
$\boldsymbol{D}_{S,t}$	=	Vector of seasonal date indicator variables
$\boldsymbol{D}_{PeakType,t}$	=	Vector of heating or cooling peak indicators
$\boldsymbol{D}_{DoW,t}$	=	Vector of Monday, Friday, and Mid-Week indicators
$\boldsymbol{D}_{LtHr,t}$	=	Indicator variable for evening winter peak
$\boldsymbol{D}_{Hol,t}$	=	Indicator variable for holiday effects
$\boldsymbol{T}_{Hot,t}$	=	Trend to account for summer air conditioning saturation
$\boldsymbol{\varepsilon}_t$	=	Error term

3. Base and Final Demand

The customer count, UPC, and peak models we described comprise the foundation of the base demand forecasts. We forecasted customer count, UPC, and peaks using model coefficient estimates and forecasted variable inputs as we described in Chapter Six: Demand Forecast. We then added various externally sourced forecasts to get the final demand forecasts. The following sections summarize the results of the component forecast models (customer counts and UPC by class) and detail how we formed the demand forecasts from their component parts.

3.1. Billed Sales Forecast

We formed the class total billed sales forecasts $\widehat{UPC}_{C,t} * D_{C,t} * \widehat{CC}_{C,t}$)by multiplying forecasted UPC and customers ($Block\ Sales_{C,t}$, then adjusting for known future discrete additions and subtractions (“$Block\ Sales_{C,t}$”).

We incorporated significant additional sales changes as additions or departures to the sales forecast as we did not reflect them in historical trends in the estimation sample period. Examples include emerging electric vehicle (EV) demand or other infrastructure projects. Finally, for the base demand forecast, we reduced the forecast of billed sales by short-term codes and standards, programmatic energy efficiency targets, and customer-owned solar ($DSR_{C,t}$) by class, using established targets in 2022–2023 and forecasts of codes and standards and customer-owned solar estimates for 2022 and 2023 from the 2021 IRP.

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

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

The details for the estimating equation components are:

t	=	Forecast time horizon
$\widehat{UPC}_{C,t}$	=	Forecast use per customer
$D_{C,t}$	=	Average of scheduled billed cycle days in class C
$\widehat{CC}_{C,t}$	=	Forecast count of customers
$DSR_{C,t}$	=	Base Forecast: codes and standards, programmatic energy efficiency targets, and customer-owned solar for 2022 and 2023
$EV_{C,t}$	=	Incremental EV sales
$Block\ Sales_{C,t}$	=	Expected entering or existing sales not captured as part of the customer count or UPC forecast

We calculated total billed sales in a month as the sum of the billed sales across all customer classes:

$$Total\ Billed\ Sales_t = \sum_{c} Billed\ Sales_{C,t}$$

3.2. Demand

We formed total system demand by aggregating individual class sales, distributing forecasted monthly billed sales into calendar sales, then adjusting for electricity losses from transmission and distribution.

The electric demand forecast ($\widehat{Demand}_{N,t}$) is the 2023 report base electric demand forecast.

The final demand forecast net of DSR will include the optimal conservation bundle calculated in the 2023 report.

3.3. Peak Demand

We forecasted electric peak hourly demand with internal and external peak demand assumptions. We employ the estimated model coefficients, normal design temperatures, and forecasted normal total system energy demand ($\widehat{Demand}_t$) less forecasted EV energy demand and short-term demand-side resources ($EV_t + DSR$) to create a peak forecast before EVs and DSR. We then adjusted this forecast with short-term forecasted peak demand-side resources ($DSR_{Peak,t}$), and forecasted EV peak demand at hour ending 18 (EV_t), to forecast total peak demand.

We removed EV and short-term DSR forecast projections from forecast normal total system energy demand in the peak hour forecast for an important reason: Energy demand DSR and EV projected MWH are distinct from peak demand DSR and EV MW and do not necessarily have the same daily demand shape as current demand on PSE's system. Thus, using the same relationships between energy demand and peak demand as of 2021 is not a valid treatment for DSR and EVs in the forecast period: Different conservation measures may have larger or small impacts on peak when compared with energy.

Thus, the peak model reflects the peak DSR assumption from short-term codes and standards and energy efficiency programs and activities, as opposed to simple downstream calculations from demand reduction. We employed this same methodology to best capture EV peak demand. We deducted EV energy demand from the base demand forecast used for peak demand forecasting, then added as a separate MW impact calculated from EV demand load shapes provided by the energy consulting firm, Guidehouse. These calculations yield system hourly peak demand in the evening each month based on normal design temperatures.

$$Peak\ Demand_t = F\left(\widehat{Demand}_{t,}, \Delta Temperature_{N,Design,t}\right) + EV_{t,HE=18} - DSR_{Peak,t}$$

$\boldsymbol{Peak\ Demand_t}$	=	Forecasted maximum system demand for month t
t	=	Forecast time horizon
$\boldsymbol{\widehat{Demand}_t}$	=	Forecast of delivered demand for month t
$\boldsymbol{\Delta Temperature_{Normal,Design,}}$	=	Deviation of peak hour/day design temperature from the monthly normal peak temperature
$\boldsymbol{EV_t}$	=	Electric Vehicle Demand at peak
$\boldsymbol{DSR_{Peak,t}}$	=	Ramped/shaped peak DSR from programmatic energy efficiency targets and short-term codes and standards effects; IRP Optimal DSR

For the electric peak forecast, we based the normal design peak hour temperature on the median (1 in 2 or 50th percentile) of seasonal minimum temperatures. The data we used to determine seasonal temperatures to reflect climate change in our forecast is a mix of historical data and future forecasted hourly temperatures, as provided by the Northwest Power and Conservation Council (NWPCC).

We netted the effects of the 2022 and 2023 conservation programs, estimated codes and standards update impacts, and customer-owned solar from the peak demand forecast to account for DSR activities already underway to reach the 2023 report's base peak demand forecast. This approach allows us to choose optimal future resources to meet peak demand. Once we determined the optimal DSR in this report, we adjusted the peak demand forecast for the peak contribution of future demand-side resources.

➔ Results of this analysis are in Chapter Six: Demand Forecast.

3.4. Hourly Demand Forecast

The AURORA portfolio analysis utilizes monthly energy and peak demand forecasts and an hourly forecast of PSE's demand. The AURORA demand forecast starts with hourly profiles. We then calibrated and shaped it to the forecasted monthly and peak demand forecasts we described. The hourly (8,760 hours + 10 days) profile starts with day one of the hourly shape as a Monday, day two as a Tuesday, and so on, with the AURORA model adjusting the first day to line up January 1 with the correct day of the week. We estimated the hourly demand shape with regression models relating observed temperatures and calendar effects to historical hourly demand data. We controlled for pandemic effects in the estimation period and suppressed them in the forecast period. We estimated demand for each hour, day of the week type (weekday, weekend/holiday), and daily average temperature type (heating, mild, cooling), yielding 24x2x3 sets of regression coefficients.

The statistical hourly regression equation summarizes the estimated demand relationships:

$$Demand_{h,d,s,t} =$$

$$\boldsymbol{\zeta_h}\left[Demand_{h-1,d,t} \quad \boldsymbol{D_{M,t}} \quad D_{Hol,d,t} \quad D_{Covid,d,t} \quad \boldsymbol{D_{DoW,d,t}} \quad \boldsymbol{T_{h,d,t}}\right] + u_{i,d,t}$$

$$\boldsymbol{T_{h,d,t}} =$$

$$\left[max(55 - T_{h,d,t}, 0) \quad max(T_{h,d,t} - 55,0) \quad max(55 - T_{h,d,t}, 0)^2 \quad D_{h=1}\, max(40 - DAvg_{t-1}, 0) \quad D_{h=1}\, max(DAvg_{t-1} - 70,0)\right]$$

$\boldsymbol{Demand_{h,d,t}}$	=	PSE hourly demand
h	=	Hour of day {1–24}
d	=	Day grouping {Weekday, Weekend/Holiday}
t	=	Date
s	=	Daily temperature grouping (heating, cooling, mild)
$\boldsymbol{\zeta_h}$	=	Vector of regression coefficients
$\boldsymbol{T_{h,d,t}}$	=	Hourly temperature at SeaTac Weather Station (KSEA)
$\boldsymbol{DAvg_{t-1}}$	=	Previous daily average temperature
$\boldsymbol{D_{M,t}}$	=	Vector of monthly date indicator variables

We forecasted an annual hourly demand profile with a future calendar of months, weekends, weekdays, and holidays and an annual 8,760-hour profile of typical normal temperatures sourced from the climate change temperature datasets described here and in Chapter Six: Demand Forecast. After we forecasted the standard demand shape, we augmented it with projected demand growth due to customer growth and increased air conditioning saturation and an hourly profile of forecasted EV demand, sourced from the consulting firm, Guidehouse.

We created the final hourly shape in the AURORA software by fully calibrating and shaping the forecasted hourly demand to forecasted monthly delivered demand ($\widehat{Demand}_{N,t}$) and monthly peak demand, as forecasted for the 2023 report base demand forecast. We used AURORA's option for Pivot High Hours, which scaled the hourly demand forecasts based on ranking and preserved low demand hours to calibrate and shape the final output.

4. Stochastic Demand Forecasts

Demand forecasts are inherently uncertain. Acknowledging this uncertainty, we considered distributions of stochastic demand forecasts in this report's models. We created two sets of stochastic demand forecasts to model these uncertainties for analyses. These energy and peak demand forecast sets are:

- The 310 electric stochastic monthly energy and peak demand forecasts that we developed for AURORA modeling
- The 90 stochastic monthly energy demand, seasonal peak demand, and hourly demand forecasts for years 2028–2029 and 2033–2034 that we used to model resource adequacy.

➔ Please see Chapter Seven: Resource Adequacy for E3's description of the methodology used to develop resource adequacy load forecasts used in the RA analysis.

Variability in the energy and peak demand forecast originates from underlying customer growth and usage uncertainty. We forecasted customer growth and usage with varying underlying driver assumptions, principally economic and demographic indicators, temperatures, EV growth, and regression model estimate uncertainty to create a distribution of potential energy and peak demand forecasts.

4.1. Economic and Demographic Assumptions

The econometric demand forecast equations depend on specific economic and demographic variables; these may 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), personal income, 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 simulations of demand. 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[3] by providing the standard errors for the quarterly growth of key U.S. macroeconomic inputs into PSE's economic and demographic models.

We based these standard errors 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 outliers from the 1,000 economic and demographic draws.

4.2. Temperature

We modeled uncertainty in the heating and cooling load levels by considering varying future years' degree days and temperatures. We randomly sourced 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.

4.3. Electric Vehicles

The team sourced high and low scenarios of EV energy and peak demand from Guidehouse in addition to the base EV demand forecast. We provide these forecasts in Chapter Six: Demand Forecast. Although the 310 stochastic demand forecasts evaluated in the AURORA modeling process include a proportional number of these high/low EV scenarios, the demand forecasts we developed for resource adequacy modeling did not.

4.4. Model Uncertainty

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

5. Climate Change Assumptions

Puget Sound Energy's demand forecasting models employ various thresholds of HDDs and CDDs, consistent with industry practices. Monthly degree days help estimate the service area's heating- and cooling-sensitive demand. Most PSE's customer classes are weather sensitive and require a degree day assumption. A degree day measures the heating or cooling severity, as 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 degree day sensitivities, which we then forecasted forward with a monthly "normal" degree day assumption. To reflect climate change in the 2023 Electric Report, we employed historically observed temperatures and forecasted temperatures derived from climate change models provided by the NWPCC. Please see Chapter Six: Demand Forecast for details of the climate change models

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

and results we incorporated. The following section discusses our methodology to create normal degree days from these various temperature sources.

5.1. Energy Forecast

We define monthly normal degree days as a rolling weighted average of the 15 years before and the 15 years after the forecast year, including the forecast year for the 2023 report. The years after historical actuals are three climate change models provided by the NWPCC. The new definition results in warmer winters, thereby decreasing total heating demand, and warmer summers, increasing cooling 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 $\boldsymbol{HDD}_{M,Base,t}$ and Cooling Degree Days $\boldsymbol{CDD}_{M,Base,t}$ for a scenario (M), Base temperature, and observation time (t) as:

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

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

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

$$\boldsymbol{DD}_{Base,t} = \begin{cases} \boldsymbol{DD}_{Actuals,Base,t}\ for\ t < Jan\ 2020 \\ \frac{\boldsymbol{1}}{\boldsymbol{3}}\left(\boldsymbol{DD}_{CanESM2,Base,t} + \boldsymbol{DD}_{CCSM4,Base,t} + \boldsymbol{DD}_{CNRM,Base,t}\right) for\ t > Dec\ 2019 \end{cases}$$

To calculate normal degree days, we calculated the average monthly degree days for the 15 years prior and 15 years forward from the given year in the forecast period, using actual temperature data through 2020 and forecasted climate projections after 2020.

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

5.2. Peak Forecast

Previous IRPs assumed an electric normal hourly peak temperature of 23 degrees, based on the 1-in-2 seasonal minimum temperatures during peak hours, hour ending (HE) 8 am–8 pm), for 30 years of history 1988–2017. To calculate the new peak temperature, we replicated and expanded the methodology used to calculate the previous peak temperature to incorporate multiple sets of climate model temperature projections and calculate peak temperatures under additional peak-specific conditions (evening-only specific peak).

5.2.1. Calculate Maximum and Minimum Temperatures in Season

For each model (M: CanESM2, CCSM4, CNRM), Year, Peak Period (All Hours: HE8–HE20 and Evening: HE17–HE19), and Season (Winter: Nov, Dec, Jan, Feb and Summer: June-September), calculate the minimum and maximum temperatures.

$$Min\ Temp_{Y,M,P=All} = \begin{cases} min\left(\boldsymbol{min(D_{H=8}\, T_{Y,Actual})}, \ldots, \boldsymbol{min(D_{H=20}\, T_{Y,Actual})}\right) & Y < Aug\ 2021 \\ max\left(\boldsymbol{min(D_{H=8}\, T_{Y,Ml})}, \ldots, \boldsymbol{min(D_{H=20}\, T_{Y,M})}\right) & Y > Aug\ 2021 \end{cases}$$

$$Min\ Temp_{Y,M,P=Evening} = \begin{cases} min\left(\boldsymbol{min(D_{H=17}\, T_{Y,Actual})}, \boldsymbol{min(D_{H=18}\, T_{Y,Actual})}, \boldsymbol{min(D_{H=19}\, T_{Y,Actual})}\right) & Y < Aug\ 2021 \\ max\left(\boldsymbol{min(D_{H=17}\, T_{Y,Ml})}, \boldsymbol{min(D_{H=18}\, T_{Y,M})}, \boldsymbol{min(D_{H=19}\, T_{Y,M})}\right) & Y > Aug\ 2021 \end{cases}$$

$$Max\ Temp_{Y,M,P=Evening} = \begin{cases} max\left(\boldsymbol{max(D_{H=17}\, T_{Y,Actual})}, \boldsymbol{max(D_{H=18}\, T_{Y,Actual})}, \boldsymbol{max(D_{H=19}\, T_{Y,Actual})}\right) & Y < Aug\ 2021 \\ max\left(\boldsymbol{max(D_{H=17}\, T_{Y,Ml})}, \boldsymbol{max(D_{H=18}\, T_{Y,M})}, \boldsymbol{max(D_{H=19}\, T_{Y,M})}\right) & Y > Aug\ 2021 \end{cases}$$

We extended the range of observed actuals for peak temperatures past calendar year-end into summer 2021 to reflect observations occurring during June 2021's Heat Dome event. We calculated additional peak temperature restrictions to reflect the time of day in which peak load typically occurs. The minimum daily temperature occurs almost exclusively during HE8 or HE9; thus, minimum temperatures calculated over all peak hours effectively represent morning peak conditions. We calculated the additional evening peak period to capture the expected peak temperature during evening peak load hours — the most common for December and summer peaks. The peak temperatures with these additional restrictions inform the evening peak demand forecast.

For each peak temperature type and period, the result will be four series (Actuals, CanESM2, CCSM4, CNRM) for each season, with observations of seasonal minimum and maximum for each year.

5.2.2. Create Samples of Minimum and Maximum Temperatures by Climate Period

Here we use the term climate period to refer to the 30-year rolling window of 15 years backward- and 15 years forward-looking data for projections. For example, in the forecast year 2024, the relevant climate period to create the sample of possible temperature outcomes is 2009 to 2038. The first forecast year that uses only climate change model projections is winter 2036.

For each peak temperature type (minimum or maximum), forecast year (T), and peak period (P), the sample population is used to determine a 1-in-2 temperature range below.

We define the sample set for each climate model by the 30 maximum and minimum temperatures by year and peak period:

$$\boldsymbol{Max\ Temp}_{T,M,P} = \{Max\ Temp_{Y=T-15,M,P}, \ldots, Max\ Temp_{Y=T+14,M,P}\}$$

$$\boldsymbol{Min\ Temp}_{T,M,P} = \{Min\ Temp_{Y=T-15,M,P}, \ldots, Min\ Temp_{Y=T+14,M,P}\}$$

The collection of sample sets defined, which span historical observations and climate models, forecast year, and peak period, defined the set we used for the distributions of peak temperature outcomes:

$$\boldsymbol{Max\ Temp}_{T,P} = \{\boldsymbol{Max\ Temp}_{T,Actual,P}, \boldsymbol{Max\ Temp}_{T,Actual,P}, \boldsymbol{Max\ Temp}_{T,Actual,P}, \boldsymbol{Max\ Temp}_{T,CANESM2,P},,, \boldsymbol{Max\ Temp}_{T,CCSM4,P}, \boldsymbol{Max\ Temp}_{T,CNRM,P}\}$$

$$\boldsymbol{Min\ Temp}_{T,P} = \{\boldsymbol{Min\ Temp}_{T,Actual,P}, \boldsymbol{Min\ Temp}_{T,Actual,P}, \boldsymbol{Min\ Temp}_{T,Actual,P}, \boldsymbol{Min\ Temp}_{T,CANESM2,P},,, \boldsymbol{Min\ Temp}_{T,CCSM4,P}, \boldsymbol{Min\ Temp}_{T,CNRM,P}\}$$

We repeated the actual observed temperature set to equally weight a year of historical observations with a year of the three future climate models because we did not aggregate the future climate models before we added them to the sample population. They have no averaging, nor did we take the minimum or maximum within individual climate model samples. This approach is the most straightforward way to not bias temperature observations towards the climate models and away from actual historical observations for appropriate climate periods. The sets $\mathbf{Max\ Temp}_{\mathrm{T,Actual}}$ and $\mathbf{Min\ Temp}_{\mathrm{T,P}}$ gradually shrink as the forecast year increases and is empty for T>2036.

5.2.3. Calculate 50th Percentile by Study Year

$$P\{Min\ Peak\ Temp_{T,P} < \boldsymbol{Min\ Temp}_{T,P}\} = 0.5$$

$$P\{Max\ Peak\ Temp_{T,P} < \boldsymbol{Max\ Temp}_{T,P}\} = 0.5$$

The resulting $Peak\ Temp_{T,P}$ for a given forecast year T (2024–2045), peak period P (all hours, evening hours), and type (minimum, maximum) is the expected temperature for which there is a 50 percent likelihood the actual peak seasonal minimum or maximum temperature will be higher or lower during the given peak period (all hours or just evening), based on the sample sets defined in the process above.

➔ Please see Chapter Six: Demand Forecast for a discussion of why climate change models are employed and why we must model an evening-specific peak event.

5.3. Hourly Forecast

We created the hourly temperature profiles by ranking days (24-hour temperature shapes) within a month by daily average temperature and then averaging the 24-hour temperature profile across relevant models. Depending on the year desired, the hourly average temperatures are an equal weighting of the 30-year rolling window of historical observations and the three climate change models. Once we created a set of typical monthly 24-hour profiles, we reordered days to typically observed monthly temperature patterns, with typical seasonal peak times (summer and winter) containing heating and cooling events consistent with the 1-in-2 peak temperature assumptions described Chapter Six: Demand Forecast.

5.3.1. Rank Monthly Temperature Observation by Daily Average Temperature

For each climate model and historical observation, rank days by daily average temperature within a month (M) and year (T), where:

$$\bar{t}_{T,M,(i)} = \sum_{h=1}^{24} Temp_{h,T,M} \text{ , } i = 1 \dots 28/30/31$$

Let (i) denote the order statistics of the daily temperature for the month:

$$\bar{\boldsymbol{t}}_{T,M} = \{\bar{t}_{T,M,(1)}, \dots, \bar{t}_{T,M,(31)}\}$$

5.3.2. Average 24-hour Profiles by Daily Rank Across Appropriate Climate Period

As we discussed, the climate period for a forecast year is a 30-year rolling window of years, weighted appropriately to not bias against the historical period for appropriate years. For a given forecast year, in a month, the temperature profile (a 24-hour vector) for the ith ranked day is defined as:

$$
\begin{aligned}
&\boldsymbol{t}_{T,(i)} \\
&= \frac{1}{2} * \frac{1}{30} \\
&* \left(\left[\sum_{C=T-15}^{T+14} Temp_{H=1,C,CANESM2,R=i} \quad \cdots \quad \sum_{C=T-15}^{T+14} Temp_{H=24,C,CANESM2,R=i} \right] \right. \\
&+ \left[\sum_{C=T-15}^{T+14} Temp_{H=1,C,CCSM4,R=i} \quad \cdots \quad \sum_{C=T-15}^{T+14} Temp_{H=24,C,CCSM4,R=i} \right] \\
&+ \left. \left[\sum_{C=T-15}^{T+14} Temp_{H=1,C,CNRM-CM5MACA,R=i} \quad \cdots \quad \sum_{C=T-15}^{T+14} Temp_{H=24,C,CNRM-CM5MACA,R=i} \right] \right) \\
&+ \frac{1}{2} \left[\sum_{C=T-15}^{T+14} Temp_{H=1,C,Actual,R=i} \quad \cdots \quad \sum_{C=T-15}^{T+14} Temp_{H=24,C,Actual,R=i} \right]
\end{aligned}
$$

5.3.3. Reorder the Daily Profile by Typical Daily Ranking

To reflect the typical progression of temperature patterns over a month, we reordered daily temperature profiles by a historical ranking of the coldest and warmest days in the month.

For a given year and month forecast year T, when n is the coldest day and 1 is the warmest day, and each $\boldsymbol{t}_{T,(i)}$ is a vector of 24 hours, an example of a typically ordered profile may be:

$$
\boldsymbol{t}_T = \begin{bmatrix} \boldsymbol{t}_{T,(2)} \\ \boldsymbol{t}_{T,(4)} \\ \cdots \\ \boldsymbol{t}_{T,(n-2)} \\ \boldsymbol{t}_{T,(n-1)} \\ \boldsymbol{t}_{T,(n)} \\ \cdots \\ \boldsymbol{t}_{T,(10)} \\ \boldsymbol{t}_{T,(14)} \\ \boldsymbol{t}_{T,(15)} \end{bmatrix}
$$

Because we expect the peak demand modeled to occur on a weekday and non-holiday, we adjusted the rankings by calendar year, so the most extreme days occur on the nearest non-holiday and mid-weekday to the warmest or coldest typical ranked day in a month.