Appendix D. Load forecast methodology

This appendix provides detail about PGE's load forecast methodology and results for the 2023 IRP.

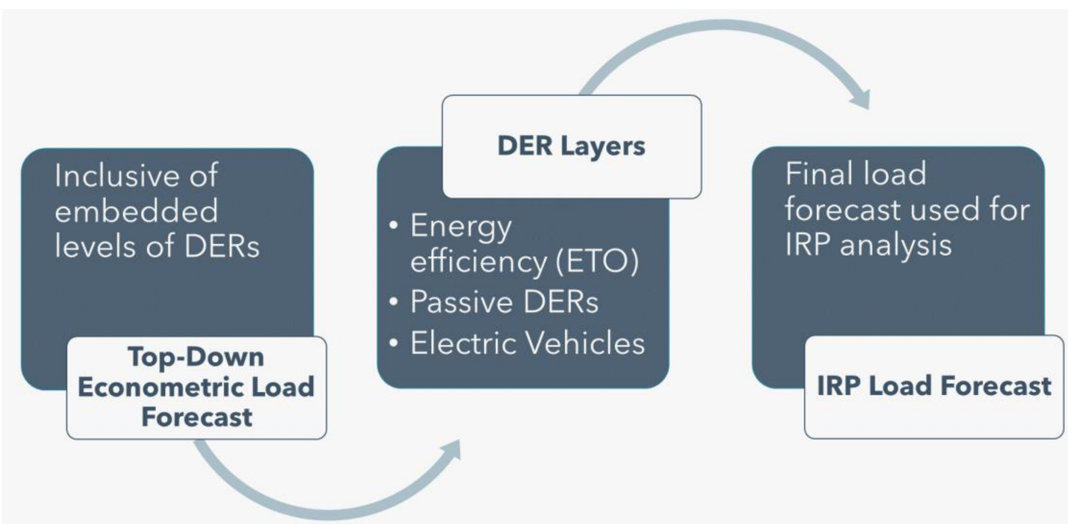
As discussed in **Section 6.2, Distributed Energy Resource (DER) impact on load**, the load forecast combines the top-down econometric forecast and the passive distributed energy resources (DER) forecast. This appendix focuses on the top-down econometric forecast models and provides annual summaries of forecast results.

Unless specified, the load values in this appendix reflect the cost-of-service supply load and do not include long-term direct access loads. The forecast vintage used is the March 2022 load forecast.

D.1 Load forecast methodology

PGE's load forecast is a compilation of several model outputs. The top-down econometric load forecast is the focus of this appendix. This is a set of models aiming to capture the relationships between PGE's energy deliveries and various structural trends and economic drivers. The impacts of DERs – primarily energy efficiency, rooftop solar, and transportation electrification – are modeled outside the top-down econometric framework and described in **Section 6.3, Load scenarios**. The incremental impacts of these loads are then 'layered' onto PGE's base forecast, as presented in **Figure 114**.

Figure 114. Load forecast methodology



PGE's top-down econometric load forecast consists of models focused on two distinct time horizons. **Table 99** describes some of the specific differences.

For the IRP process, PGE updates its long-term models to estimate growth rates for aggregated customer classes: residential, commercial, and industrial. However, the forecast result is dependent on the estimation of the near-term models as a starting point. The long-term growth rates described in this appendix are applied to the result of the near-term forecast model. The near-term model is focused on capturing near term business cycle impacts and individual forecasts for large projects. This model is submitted in PGE's general rate case (GRC) and annual update tariff (AUT) filings.

Table 99. Near term- vs. long-term model

Near Term (1-5 Years)	Long-Term (5+ Years)
25 regression-based monthly energy deliveries models Business cycle influences energy deliveries Individual customer forecast for ~25 large customers Historic data from 2010 to 2021 Explicitly removes incremental energy efficiency Updated as frequently as every quarter	Convergence to long-term growth rates, agnostic to the business cycle and specific customer growth. Three aggregated customer class growth rate models. Historic data from 2000 to 2021. Assumes energy efficiency is embedded in growth rates. Growth rates are appended to near-term model output. Updated annually to support IRP.

D.1.1 Refinements since last IRP

Development of PGE's econometric load forecast reported in this IRP began in 2020 with a review of critical models and an assessment of key issues raised by stakeholders during the 2019 IRP process.

In October 2020, at IRP Roundtable 20-6,[431] we discussed the impacts of COVID-19 on energy deliveries and out-of-model adjustments made in the near-term load forecast to account for those impacts. We also presented the testing of alternate economic drivers,

[431] Oct. 28, 2020, IRP Roundtable 20-6: https://assets.ctfassets.net/416ywc1laqmd/2XkzCQDPsoEmae8kJn5ckD/6c2e1f9462d8cc16ce8ec7752e57d67a/irp-roundtable-20-6.pdf

particularly focusing on the use of local drivers, for the industrial forecast model in response to feedback from CUB in LC-73.

In July of 2021, at IRP Roundtable 21-5,[432] we presented the preliminary long-term and peak demand models, recommended alternative industrial drivers - including benchmarking to utility peers – and requested feedback on driver selection and scenarios inputs.

In April of 2022, at IRP Roundtable 22-3,[433] we presented the final model results reflecting the March 2022 econometric load forecast and comparison to the 2019 IRP Update.[434]

Several refinements are reflected in the latest models.

- **COVID-19 Indicator**: For the 2019 IRP Update, PGE utilized out-of-model adjustments to account for the impact of COVID-19 in the near-term models. This method was purely pragmatic, an approach to manage the extreme effects quickly. Since that time, we have implemented a more robust approach to account for the impacts of COVID-19 in the econometric model via an indicator variable in the regression analysis. A further explanation of this process can be found in **COVID-19 Impact on short-term energy use.**
- **Industrial Driver**: PGE tested several local and national economic drivers for its industrial model. Variables tested included: US Gross Domestic Product (GDP), Total Oregon Income, Mean Oregon Income, Total Non-Farm Oregon Employment, Oregon GDP, and county-level GDP for PGE's service territory. Total Oregon Income was found to have the most robust relationship with PGE's industrial energy deliveries and was selected as the primary driver for the long-term industrial model.
- **Peak Demand Model Structure**: PGE separated the peak model into two seasonal models; separate cooling and heating models allow for individual seasonal-level model specifications. The peak model specification can be found in **Section D.1.5, Peak model**.

[432] July 22, 2021, IRP Roundtable 21-5: https://assets.ctfassets.net/416ywc1laqmd/2eI3mKz2HVK1uEPogSDofW/09fbb8476086009ffe7d181dfb95dc12/IRP_Roundtable_July_21-5.pdf
[433] Apr. 14, 2022, IRP Roundtable 22-3: https://assets.ctfassets.net/416ywc1laqmd/2e732S4plWpR59ID7ZDV8q/270c1816f005d6816e63ac88e9e61879/IRP_Roundtable_June_22-5.pdf
[434] PGE'S 2019 IRP Update: https://assets.ctfassets.net/416ywc1laqmd/7JkfpRUwMrqCwfKsxAPG3g/9703398aa3212f8532ffb5ced616af87/2019-irp-update-04-20-2021.pdf

D.1.2 Inputs

Normal weather assumption

The COVID-19 pandemic has shifted energy usage in several ways. Residential usage experienced a significant increase, while in the commercial segment, initial shutdowns had a stark – but short-lived - impact on energy deliveries. PGE's industrial segment was impacted least by COVID-19 and has grown dramatically since the 2019 IRP. Recent trends impact the near-term forecast, which is the starting point for the long-term forecast.

PGE assumes normal weather year as an input to the load forecast rather than a weather forecast. Weather variability different from the normal weather assumption is expected. The intention is to use an unbiased weather assumption such that the actual weather is warmer or cooler than normal 50 percent of the time. PGE uses a trend to create the forward-looking normal weather assumption that reflects the gradually warming climate. The methodological approach continues the trend observed since 1975, using data since 1941 to "hinge" the initial point of that trend.[435] **Figure 115** shows historical actual and forward-looking normal for heating and cooling degree days (HDD and CDD)[436] using this methodology.

A review was performed in the 2023 IRP to compare this input assumption to specific Representation Concentration Pathway (RCP) Climate Change Scenarios. This review finds PGE's methodology to fit within the reasonable bounds of this scenario analysis. This is described further at the end of this appendix section.

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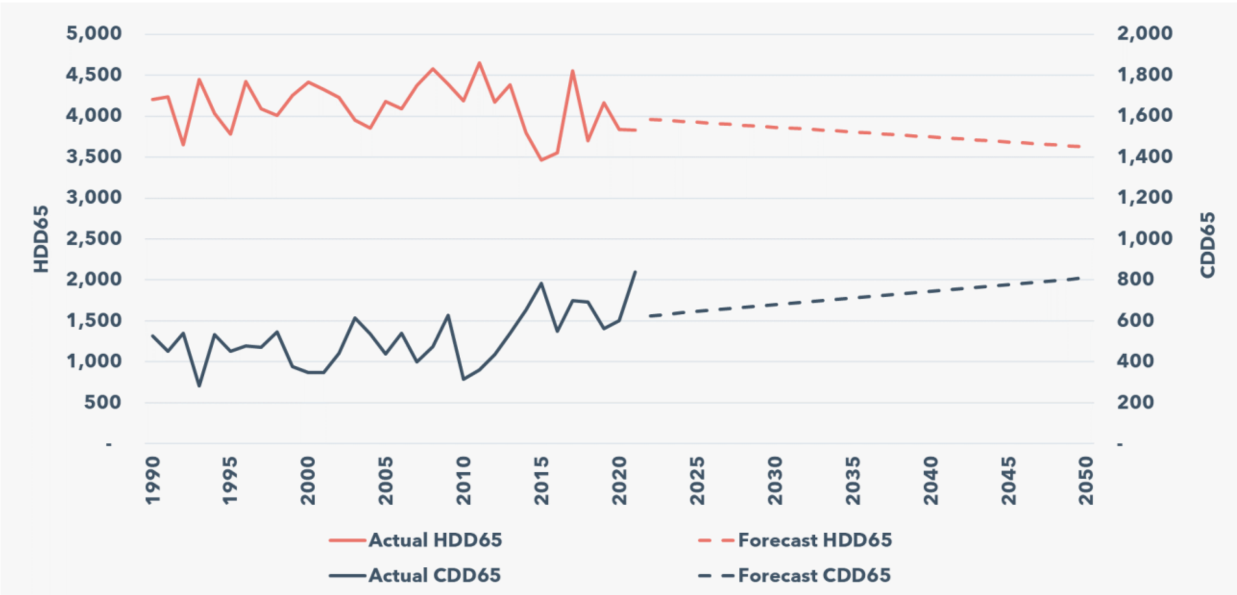
[435] Livezey, Robert E., *et al.* "Estimation and extrapolation of climate normals and climatic trends." *Journal of Applied Meteorology and Climatology* 46.11 (2007): 1759-1776. https://journals.ametsoc.org/doi/pdf/10.1175/2007JAMC1666.1

[436] Heating and cooling degree days (HDD and CDD) are the number of degrees that a day's temperature deviates from the temperature set point. For heating degree days, the measurement represents the extent to which a building would need to be heated to reach the temperature set point, and for cooling degree days, the measurement represents the extent to which a building would need to be cooled to reach the temperature set point. For these regressions with monthly data, HDD and CDD are summed for all days in the month. As an example, on a day with an average temperature of 75° F, HDD65 = 0 and CDD65 = 75 - 65 = 10.

Figure 115. Normal weather expectation in terms of heating degree days and cooling degree days



COVID-19 Impact on short-term energy use

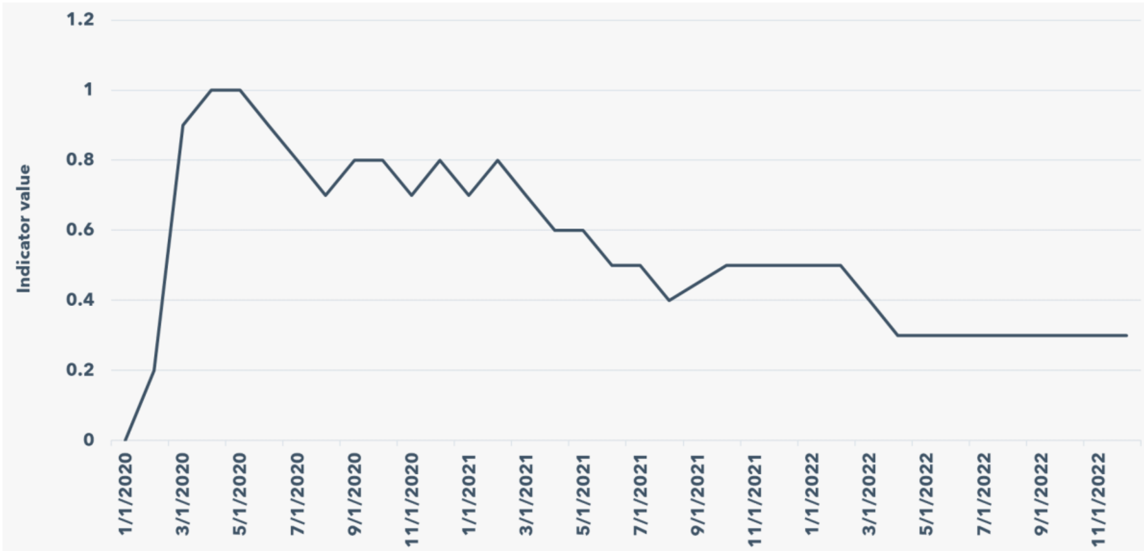
To account for changes in usage, PGE utilized a COVID-19 indicator variable based on the percent of work from home in Oregon produced by the Oregon Office of Economic Analysis.[437] The indicator variable is designed to range from 0 to 1, work from home peaked in May 2020, and that level was set to "1". The indicator was then scaled down based on monthly work from home compared to the May 2020 level. **Figure 116** presents the COVID-19 variable assumptions.

This variable was used in the residential model to account for the increase in usage and in the commercial model to account for the lower usage associated with the COVID-19 pandemic. Recent trends show that COVID-19 has permanently changed the way residential customers use energy. For the forecast, PGE assumed a slow decrease in work from home until April 2022, when long-term equilibrium will be reached at 0.3. This assumes that residential usage will remain elevate at 30 percent of the peak impact of COVID-19.

For the long-term models this variable is phased out in the long-term and does not impact the long-term growth rate beyond correcting the model fit in the short term.

[437] Lehner, Josh. "Just How Much is Working from Home on the Rise?" Available at: https://oregoneconomicanalysis.com/2021/12/16/just-how-much-is-working-from-home-on-the-rise/

Figure 116. COVID-19 indicator variable

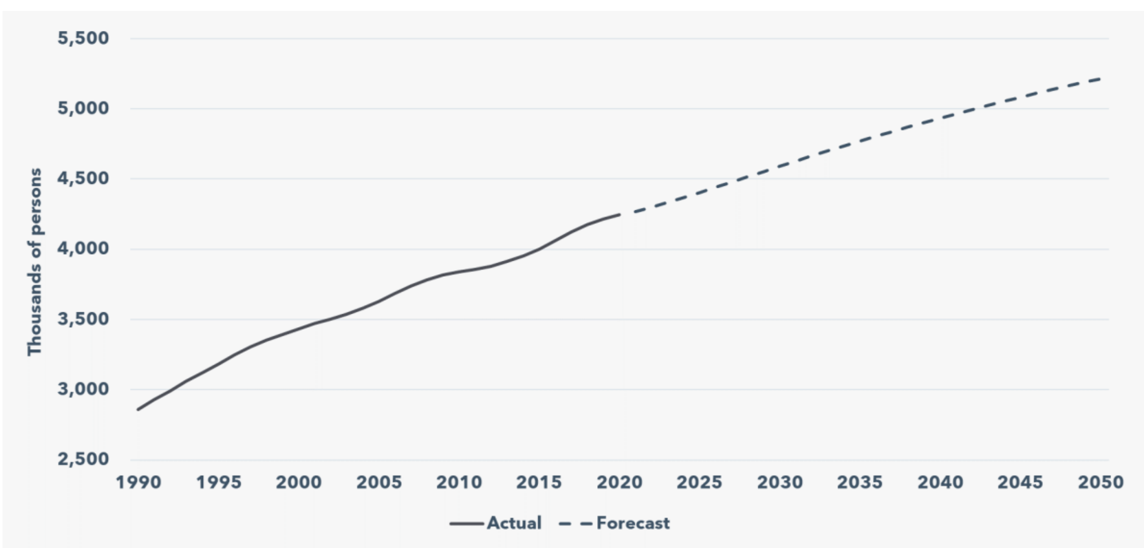


Long-term macroeconomic drivers

Oregon Population

Oregon's Population is closely related to the number of households in PGE's service area. It is used as a driver of residential customer count in PGE's residential energy deliveries model. PGE uses the Oregon Office of Economic Analysis's forecast of Oregon Population, extrapolated from 2030 to 2050. The projected average annual growth rate from 2022 to 2050 is 0.7 percent. **Figure 117** shows the historical actual and projected population levels.

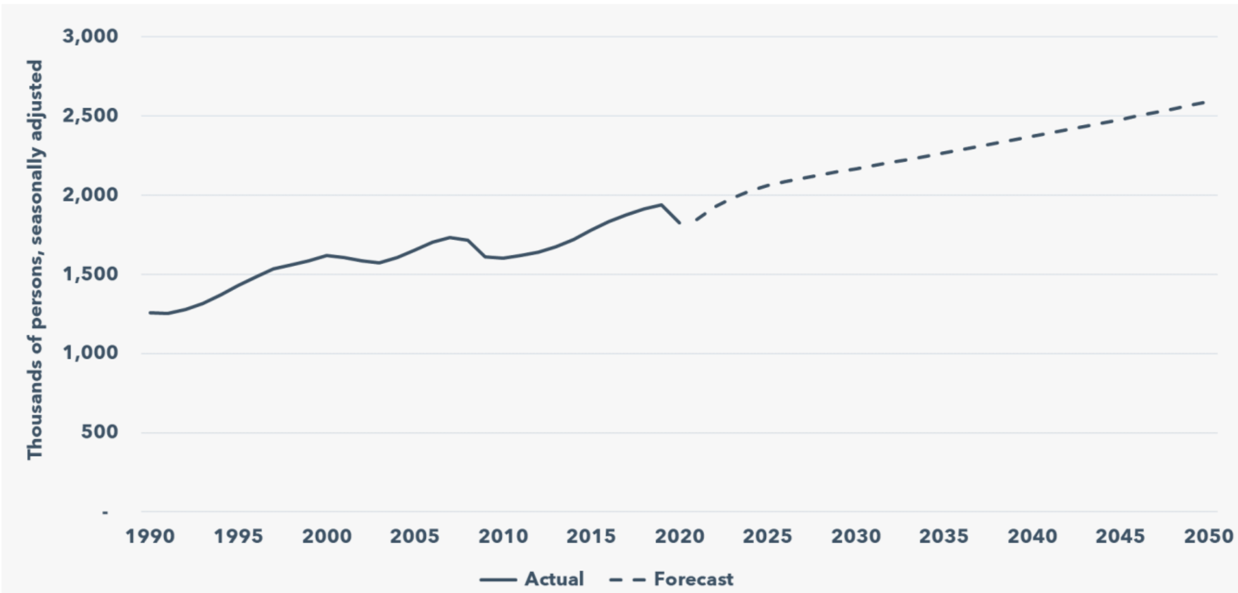
Figure 117. Oregon population



Oregon total non-farm employment

The level of employment in Oregon is the economic driver of PGE's commercial energy deliveries forecast. PGE uses the Oregon Office of Economic Analysis's forecast of employment, extended to 2050. The projected average annual growth rate from 2022 to 2050 is 0.9 percent. **Figure 118** shows the historical actual and forecasted levels of Total Non-Farm Employment.

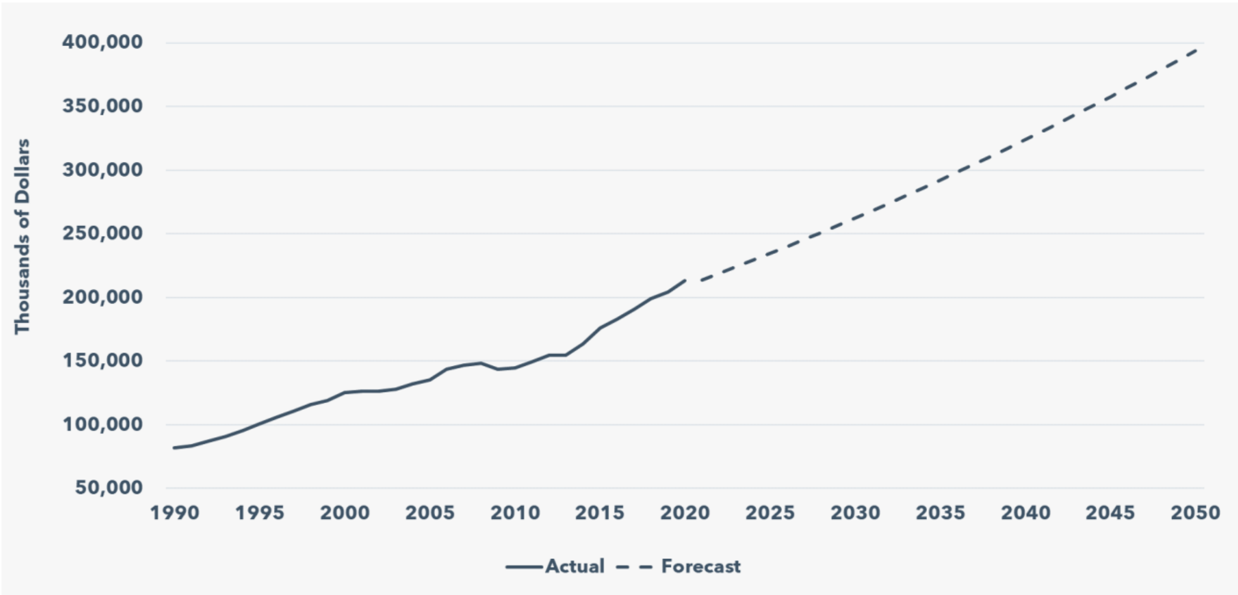
Figure 118. Oregon's total non-farm employment



Oregon Total Personal Income

Oregon's Total Personal Income is the economic driver of PGE's industrial energy deliveries forecast. Total Personal Income is income of individuals from wages, salaries, business ownership, interest and dividends, Social Security, and other government benefits. Measures of income are often used as an indication of financial health. PGE uses the vendor provided forecast released by Woods and Pool in 2021 for this input assumption. The projected average annual growth rate from 2021 to 2050 is 2.1 percent. **Figure 119** shows the historical actual and forecasted Total Personal Income.

Figure 119. Oregon total personal income



D.1.3 Model development and evaluation

In response to OPUC Staff feedback in PGE's 2016 Integrated Resource Plan and as part of continual methodology refinement, PGE worked to standardize and more formally document its model development process and evaluation criteria.[438]

A series of testing steps are used to develop long-term forecast models. This testing includes a univariate review of the underlying structure of the energy deliveries time series; an examination of the relationship between energy deliveries to drivers, including weather variables; and the testing of alternative model structures, including naïve, differenced, and "automatic" ARIMA. The model fit statistics, coefficients, and residuals are reviewed to compare and select alternate models.

- **Univariate analysis**. Univariate analysis of historical sector-level time series is conducted to identify trends, seasonality, cycles, breaks, and outliers. The first step is to inspect the data series visually. Then the autocorrelation of the series is reviewed, and statistical tests such as the Augmented Dickey Fuller (ADF) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) tests are used to assess the underlying structure of the data. When tests imply non-stationarity in a variable, PGE explores data transformations, trend variables, and naïve forecasts.

[438] Staff Comments available at: https://edocs.puc.state.or.us/efdocs/HAC/lc66hac143454.pdf

- **Weather responsiveness**. Scatter plots and testing in the regression models are used to determine the appropriate HDD and CDD variables for inclusion in each model. **Figure 120** shows the weather responsiveness of the three long-term models with monthly energy deliveries plotted against average monthly temperature using data since 2000.

In **Figure 120**, the scatter follows a relatively tight "U" shape, indicating that residential energy usage increases as the average temperature falls under 60˚F and as the average temperature is higher than 65˚F. This implies using an HDD variable calculated from a 60˚F base and a CDD variable with a 65˚F base. In (b), commercial energy deliveries increase as the average temperature falls under 50˚F and when the average temperature is higher than 60˚F. In (c), the broad scatter implies that energy deliveries to the industrial class have no significant weather dependence.

- **Residual review**. PGE reviews the autocorrelation and normality of residuals in the models for any alternative model structures considered. Ideally, residuals are white noise, meaning they are uncorrelated, have a mean of 0, have constant variance, and are normally distributed. The extent to which residuals of a regression statistically differ from white noise indicates the potential to improve the model specification. Residuals that are meaningfully correlated might lead to the addition of autoregressive or moving average terms to the model or re-visiting the regression model specification.
- **Alternate forecasts and out-of-sample testing**. PGE reviews a variety of alternate model specifications for each of the forecast groups. Testing includes: 1) models using a variety of economic drivers, as well as those with no economic driver; 2) models with and without monthly indicator variables; and 3) models using a variety of data transformations. As part of the standardization of the model evaluation and to benchmark against the most simplistic models, PGE also tests naïve and seasonally naïve forecasts. Out-of-sample testing, which uses a training period to estimate the model and a testing period to evaluate model performance, was included as a part of PGE's testing process in the 2019 IRP Load Forecasting Appendix. While PGE intends to employ this method in the future, out-of-sample testing was not performed for the forecast vintage used in this IRP. PGE did not perform out-of-sample testing because the dramatic but short-lived period of impact for the COVID-19 indicator variable did not allow for a long enough period to reflect useful testing.

D.1.4 Long-term energy models

Residential model

The long-term residential energy deliveries model, shown in **Equation 1**, comprises of forecasts for both customer count, an annual model based on Oregon Population (**Equation 3**), and use-per-customer, a monthly model based on relationships to Oregon Total Non-Farm employment, COVID-19, and heating and cooling degree days (**Equation 2**). The resulting monthly use-per-customer forecast is combined with the annual customer count forecast for a monthly forecast of residential energy deliveries.

Equation 1. Residential energy deliveries

$$kWh_{res} = UPC_{res} * CC_{res}$$

Where:

- UPC = Use-per-customer
- CC = Customer count

Equation 2. Residential use-per-customer

$$UPC_{res,t} = \sum_{k=0}^{11} (\beta_k\, Month_k + \alpha_k Trend_k) + \beta_{12} HDD60 + \beta_{13} CDD65 + \beta_{14} COVID\ Indicator_t + \beta_{15} UPC_{res,t-1} + \varepsilon_t$$

Where:

- HDD60 = Heating degree day with 60° F set point
- CDD65 = Cooling degree day with 65° F set point
- Trend = Numerical variable that increases by 1 each year
- COVID Indicator = Indicator variable between 0 and 1
- ε_t= error term

Equation 3. Residential customer count

$$\Delta CC_{res,t} = \beta_0 + \beta_1 * \Delta POP_{or} + \beta_2 \sum_{n=1}^{12} \frac{CC_{res.n}}{\sum_{n=1}^{12} n + \varepsilon_t}$$

Where:

- $\Delta y = y_{t-} y_{t-1}$ representing a first-order difference
- POP_{OR} = Oregon Population
- ε_t= error term

Commercial model

The commercial energy deliveries model, shown in **Equation 4**, is a monthly model that establishes a relationship between commercial energy deliveries and Oregon's Total Non-Farm employment, COVID-19, and heating and cooling degree days.

Equation 4. Commercial energy deliveries

$$kWh_{com,t} = \sum_{k=0}^{11} \beta_k\, Month_k + \beta_{12} HDD50 + \beta_{13} CDD60 + \beta_{14} COVID\ Indicator_t + \beta_{15}\, OENTNA + \beta_{16}\, kWh_{com,t-1} + \varepsilon_t$$

Where:

- HDD50= Heating degree day with 50° F set point
- CDD60 = Cooling degree day with 60° F set point
- COVID Indicator = Indicator variable between 0 and 1
- OENTNA = Oregon's Total Non-Farm employment
- ε_t = error term

Industrial model

The annual industrial model includes Oregon's Total Personal Income as a driver of energy deliveries (**Equation 5**).

Equation 5. Industrial energy deliveries

$$\Delta kWh_{ind,t} = \beta_0 + \beta_1 X \Delta Personal\ Income + \beta_2 \sum_{n=1}^{12} \frac{kWh_{ind,n}}{\sum_{n=1}^{12} n + \varepsilon_t}$$

Where:

- $\Delta y = y_{t-} y_{t-1}$ representing a first-order difference
- Personal Income= Oregon's Total Personal Income
- ε_t= error term

D.1.5 Peak model

The peak models, shown in **Equation 6 and 7. Peak Demand**, are a monthly seasonal model that relates the single-hour peak demand of PGE's net system (in MW) to average monthly demand (in MWa) and weather variables. The models consider the impact of heating and cooling degree days (HDD and CDD), as well as the summer model, which accounts for the growing saturation of air conditioning in the home in PGE's service area. Both models include the previous day's temperature impacts by using cooling or heating degree days, and the winter model includes wind speed.

Equation 6 and 7. Peak Demand

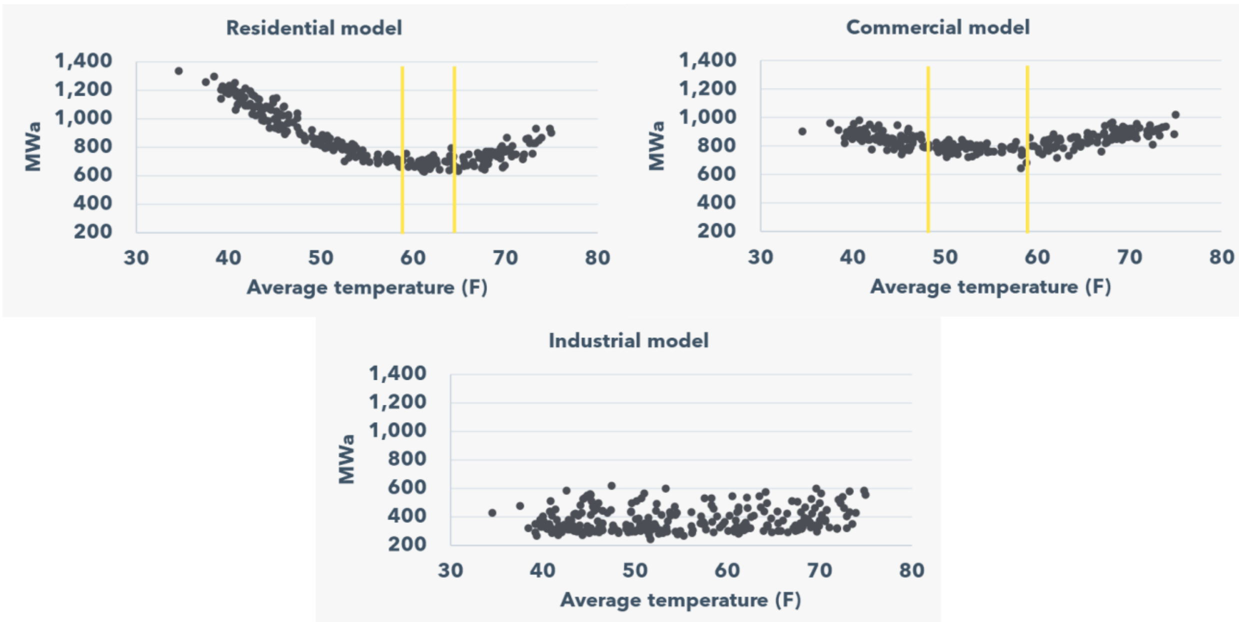
$$MW_{summer,t} = \beta_1 PKDAYCDD + \beta_2 PDCDD + \frac{\beta_3 ACSAT * NRC1_t}{1000} + \beta_4 CycleMA_t + \beta_5 CDD65 + \beta_6 May + \beta_7 Jun + \beta_8 Jul + \beta_9 Aug + \beta_{10} Sep + \beta_{11} Weekend + \varepsilon_t$$

$$MW_{winter,t} = \beta_1 PKDAYHDD + \beta_2 PDHDD + \beta_3 PKDAYWIND + \beta_4 CycleMA_t + \beta_5 HDD60 + \beta_6 Oct + \beta_7 Nov + \beta_8 Dec + \beta_9 Jan + \beta_{10} Feb + \beta_{11} Mar + \beta_{12} Weekend + \beta_{13} STEP0811 + \varepsilon_t$$

Where:

- MWa = Average monthly demand
- PKDAYCDD = CDD with 65° F set point on the day the peak occurred
- PDCDD = CDD with 65° F set point on the day before the day the peak occurred
- NRC1 = Count of residential customers
- ACSAT = Percentage of households with air conditioning
- CycleMA = Twelve months moving average of total monthly usage
- PKDAYHDD = HDD with 65° F set point on the day the peak occurred
- PDCDD = HDD with 65° F set point on the day before the day the peak occurred
- PKDAYWIND = Average daily wind speed on the day the peak occurred
- STEP0811 = An indicator variable beginning in November 2008
- ε_t = error term

Figure 120. Weather sensitivity of energy deliveries to (a) the residential class, (b) the commercial class, and (c) the industrial class



D.1.6 Probabilistic loads

All forecasts are subject to uncertainty, including uncertainties associated with forecasts of the input variables and the complexity of the estimated relationships with those variables. Some of these uncertainties can be characterized quantitatively using model parameters.

The single most important driver of load variability is the weather. Residential and small commercial loads are particularly sensitive to the weather due to heating and cooling loads. Weather is known to be highly variable from one year to the next. PGE addresses the stochastic risk in the load forecast associated with weather, analyzing 30 years of weather variability in its Resource Adequacy model, described in **Chapter 6, Resource needs.**

Two sources of uncertainty characterized using the output statistics of the regression models described previously are model uncertainty and coefficient uncertainty. Model uncertainty is the standard error of the regression or a reflection of how the model performs over the period of data used to inform the model. Coefficient uncertainty is the standard error associated with the estimated coefficient, which defines the relationship between the dependent and driver variables.

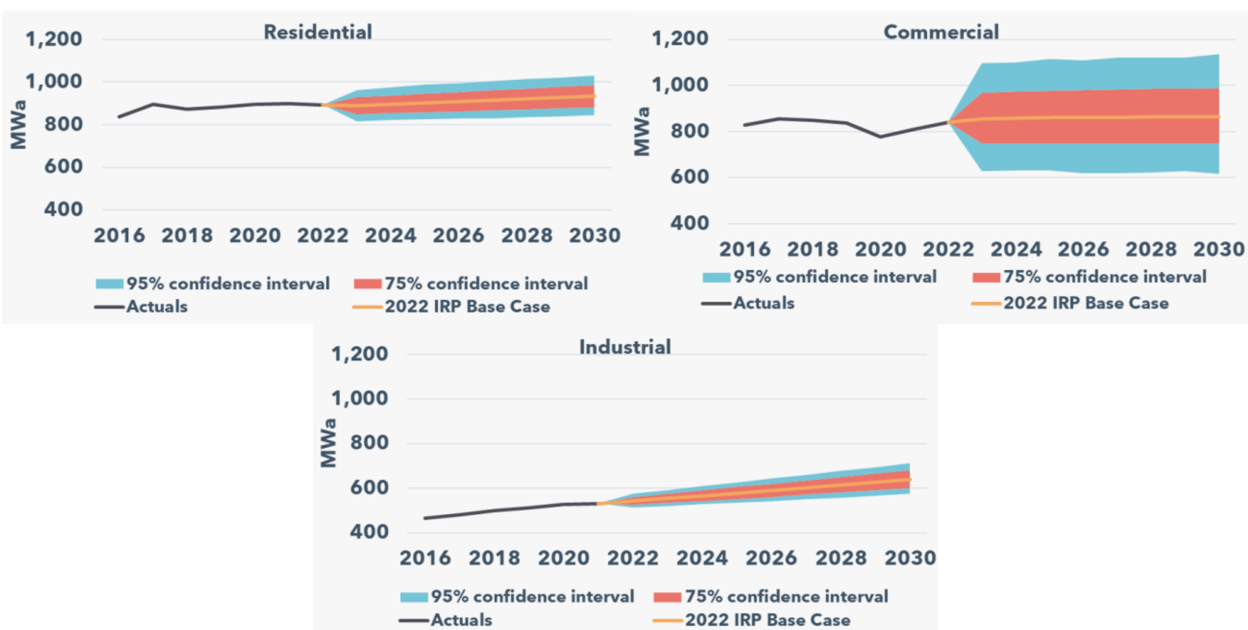
EViews, a statistical package used primarily for time-series oriented econometric analysis, and also the software package PGE uses to conduct its load forecast, was used to run stochastic simulations that combine model uncertainty and coefficient uncertainty to create confidence bands around the base case forecast. During simulation runs, coefficients are randomly varied along with residuals, and the errors are quantified and used to obtain confidence intervals. Over 10 thousand simulations were run for each of the long-term regression models.

Figure 121 shows the 75 and 95 percent confidence bounds on the three energy deliveries models.

Another category of uncertainty relates to the driver variables used in the regression models. Uncertainties in the forecast of the economic driver variables are considered by scenario analysis, described further in **Chapter 6, Resource needs**.

Other uncertainties not quantified by this approach yet worth mentioning relate to variables excluded from the models and the estimation periods of the models. For example, specific large load might cause shifts in load that cannot be precisely timed by a driver-based model. A model is, by design, a simplification of reality. The interdependencies of energy deliveries are complex and widespread across the macroeconomy. The benefits and uncertainties of different variable selection and estimation periods are weighed during the model development and evaluation process. Drivers which may impact loads outside of this modeling process may be considered in scenario analysis outside of the modeled uncertainties.

Figure 121. Confidence interval on the net system residential (left), commercial (right), and industrial (low) energy deliveries models



D.2 Results

Results of the top-down econometric models described previously are combined with explicit forecasts for EE, EV, and behind-the-meter solar and storage to arrive at the total load scenarios shown in the following tables. These load forecasts do not include long-term direct access loads, consistent with Guideline 9.[439] This section provides low, reference, and high forecasts for Net System Load by residential, commercial, and industrial customers. Net System Load includes both cost-of-service supply customers, long-term direct access customers and new load direct access customers.

D.2.1 Energy load forecasts

Table 100 summarizes the load forecast scenarios for energy deliveries (in MWa) at the bus bar.[440]

Table 101, **Table 102**, and **Table 103** provide the annual forecasts for the reference, low, and high scenarios. For these tables, note that passive DER only captures the forecasts for generation from distributed PVs.

Table 100. Load forecast scenarios in MWa[441]

	Low Need			Reference Case			High Need		
	2023	2043	AAGR	2023	2043	AAGR	2023	2043	AAGR
Top-down Load Forecast	2,351	3,644	2%	2,365	3,970	3%	2,378	4,276	3%
Base Load Forecast	2,320	3,054	1%	2,334	3,407	2%	2,347	3,731	0
Energy Efficiency	-31	-590	0	-31	-563	0	-31	-546	17%
Rooftop PV	-1	-81	28%	-1	-50	28%	-1	-28	22%
Building Electrification	4	86	17%	4	87	17%	4	124	20%

[439] Order No. 07-002 at 19, see Guideline 9, as amended by Order No. 07-047 at Appendix A, p.6
[440] As mentioned previously, the load forecasts in this section do not include long-term direct access loads.
[441] The base load forecast is the top-down load forecast adjusted to exclude the impacts of the cost-effective deployable EE savings and the assumptions for the embedded distributed PV generation and electric vehicle load. The EE savings are cumulative values adjusted for line losses and intra-year deployment beginning in 2022. Note that in this and the following tables the AAGR is not calculated because savings before 2020 are not reported in these values.

	Low Need			Reference Case			High Need		
	2023	2043	AAGR	2023	2043	AAGR	2023	2043	AAGR
Transportation Electrification	13	372	18%	15	504	20%	16	590	20%
Total Load Forecast	2,305	2,841	1%	2,321	3,385	2%	2,336	3,870	3%

Table 101. Reference case load scenario with layers, MWa

Year	(a) Base load	(b) Energy Efficiency	(c) Transportation Electrification	(d) Rooftop PV	(e) Building Electrification	(f) = (a) + (b) + (c) + (d) + (e) Total Load
2023	2,334	-31	15	-1	4	2,321
2024	2,402	-61	21	-1	7	2,367
2025	2,463	-91	28	-3	10	2,407
2026	2,530	-121	38	-5	13	2,455
2027	2,594	-151	48	-8	17	2,500
2028	2,649	-181	60	-12	20	2,535
2029	2,703	-214	73	-18	23	2,567
2030	2,759	-247	91	-25	27	2,605
2031	2,817	-282	115	-31	31	2,650
2032	2,875	-316	139	-37	35	2,696
2033	2,931	-348	166	-41	40	2,747
2034	2,986	-378	196	-42	44	2,804
2035	3,040	-408	224	-43	48	2,861
2036	3,093	-435	266	-44	53	2,932
2037	3,143	-460	296	-45	57	2,992
2038	3,192	-483	327	-45	61	3,052
2039	3,237	-502	365	-46	66	3,120
2040	3,280	-518	405	-47	72	3,192

Year	(a) Base load	(b) Energy Efficiency	(c) Transportation Electrification	(d) Rooftop PV	(e) Building Electrification	(f) = (a) + (b) + (c) + (d) + (e) Total Load
2041	3,323	-533	440	-48	77	3,258
2042	3,361	-545	457	-49	80	3,304
2043	3,407	-563	504	-50	87	3,385
Average annual growth rate	2%	N/A	20%	28%	17%	2%

Table 102. Low Case load scenario with layers, MWa

Year	(a) Base load	(b) Energy Efficiency	(c) Transportation Electrification	(d) Rooftop PV	(e) Building Electrification	(f) = (a) + (b) + (c) + (d) + (e) Total Load
2023	2,320	-31	13	-1	4	2,305
2024	2,373	-61	18	-2	7	2,336
2025	2,419	-91	24	-4	10	2,358
2026	2,471	-121	31	-7	13	2,388
2027	2,520	-152	38	-11	17	2,412
2028	2,558	-184	46	-16	20	2,425
2029	2,596	-217	55	-23	23	2,434
2030	2,637	-252	68	-33	27	2,446
2031	2,678	-288	84	-43	31	2,463
2032	2,719	-323	100	-52	35	2,479
2033	2,758	-357	118	-58	39	2,501
2034	2,796	-389	138	-60	44	2,529
2035	2,833	-420	157	-63	48	2,555
2036	2,869	-449	185	-65	53	2,593
2037	2,901	-476	207	-67	57	2,622
2038	2,932	-502	230	-69	61	2,652

Year	(a) Base load	(b) Energy Efficiency	(c) Transportation Electrification	(d) Rooftop PV	(e) Building Electrification	(f) = (a) + (b) + (c) + (d) + (e) Total Load
2039	2,959	-523	257	-72	66	2,688
2040	2,984	-542	288	-75	72	2,728
2041	3,007	-558	317	-77	77	2,767
2042	3,027	-570	333	-79	80	2,791
2043	3,054	-590	372	-81	86	2,841
Average annual growth rate	1%	N/A	18%	28%	17%	1%

Table 103. High Case load scenario with layers, MWa

Year	(a) Base load	(b) Energy Efficiency	(c) Transportation Electrification	(d) Rooftop PV	(e) Building Electrification	(f) = (a) + (b) + (c) + (d) + (e) Total Load
2023	2,347	-31	16	-1	4	2,336
2024	2,428	-61	24	-1	7	2,397
2025	2,503	-91	33	-1	11	2,454
2026	2,585	-121	44	-2	15	2,522
2027	2,664	-150	56	-2	20	2,587
2028	2,733	-180	71	-3	24	2,645
2029	2,802	-212	88	-3	29	2,704
2030	2,873	-243	110	-3	34	2,771
2031	2,946	-276	140	-4	40	2,846
2032	3,019	-309	172	-5	46	2,923
2033	3,091	-340	207	-5	52	3,005
2034	3,163	-369	248	-6	58	3,094
2035	3,233	-396	287	-7	64	3,181
2036	3,302	-421	340	-8	72	3,285

Year	(a) Base load	(b) Energy Efficiency	(c) Transportation Electrification	(d) Rooftop PV	(e) Building Electrification	(f) = (a) + (b) + (c) + (d) + (e) Total Load
2037	3,368	-445	378	-10	78	3,370
2038	3,433	-467	415	-12	85	3,454
2039	3,494	-485	457	-15	92	3,544
2040	3,553	-502	499	-18	101	3,635
2041	3,613	-517	534	-21	109	3,718
2042	3,668	-528	544	-25	114	3,774
2043	3,731	-546	590	-28	124	3,870
Average annual growth rate	2%	N/A	20%	22%	20%	3%

D.2.2 Peak load forecasts

Table 104 provides the seasonal peak loads for each year and Need Future.[442] These tables reflect total load values; the top-down econometric forecast combined with the forecasts for EVs and building electrification. This forecast includes costs effective energy efficiency but does not include the impacts of passive or active demand response programs. The values in this table are reflective of the loads used in the Sequoia model, which has 30-years (1992-2021) of weather variation included (median peak loads are shown).

Table 104. Peak load forecast by Need Future and season, MW

Year	Low Need		Reference Need		High Need	
	Summer	Winter	Summer	Winter	Summer	Winter
2023	3,712	3,510	3,726	3,525	3,740	3,541
2024	3,746	3,547	3,776	3,580	3,805	3,613
2025	3,781	3,583	3,828	3,635	3,874	3,689
2026	3,822	3,626	3,888	3,699	3,953	3,774

442 As mentioned previously, the load forecasts in the section do not include long-term direct access loads.

Year	Low Need		Reference Need		High Need	
	Summer	Winter	Summer	Winter	Summer	Winter
2027	3,861	3,668	3,948	3,766	4,032	3,864
2028	3,890	3,706	4,001	3,831	4,105	3,954
2029	3,924	3,734	4,061	3,885	4,188	4,036
2030	3,960	3,773	4,124	3,954	4,277	4,136
2031	4,002	3,814	4,195	4,030	4,376	4,244
2032	4,043	3,861	4,269	4,111	4,481	4,363
2033	4,095	3,908	4,355	4,198	4,602	4,492
2034	4,145	3,964	4,442	4,292	4,729	4,632
2035	4,200	4,020	4,535	4,389	4,860	4,773
2036	4,256	4,081	4,630	4,493	4,994	4,921
2037	4,319	4,139	4,732	4,592	5,130	5,058
2038	4,380	4,203	4,830	4,697	5,259	5,198
2039	4,442	4,267	4,930	4,801	5,383	5,329
2040	4,506	4,336	5,027	4,904	5,500	5,456
2041	4,576	4,402	5,128	5,002	5,616	5,573
2042	4,643	4,472	5,223	5,102	5,723	5,689
2043	4,709	4,540	5,316	5,197	5,824	5,797
Annual average growth rate	1.2%	1.3%	1.8%	2.0%	2.2%	2.5%

D.3 Net system load

Net System Load includes both cost-of-service supply customers and direct access customers. While Net System Load is not used in the IRP need assessments or portfolio analysis, the information in this section is provided for reference as it reflects the level of disaggregation at which the load forecast analysis occurs.

Table 105, **Table 106**, and **Table 107** provide the reference, low, and high econometric load forecasts for Net System Load in MWa at the bus bar by class. The commercial class includes street and highway lighting, and the industrial class consists of both transmission and primary-level customers. The high and low scenarios capture high and low growth conditions and +/- 1 standard deviation of uncertainty from the regression model parameters. These forecasts do not include the impacts of the explicit forecasts for Energy Vehicles (EVs), Distributed Energy Resources (DERs), or additional Energy Efficiency (EE) savings beyond Energy Trust's projections.

Table 105. Econometric Net System Load with reference growth conditions, MWa

Year	Residential	Commercial	Industrial	Total
2022	933	802	503	2,239
2023	922	815	566	2,303
2024	918	808	615	2,341
2025	914	801	657	2,372
2026	913	794	703	2,409
2027	915	786	743	2,444
2028	921	786	760	2,467
2029	928	788	772	2,489
2030	935	790	787	2,512
2031	942	791	802	2,535
2032	949	792	818	2,559
2033	956	793	834	2,583
2034	963	795	850	2,607
2035	970	796	866	2,632
2036	977	797	883	2,657
2037	984	798	900	2,683
2038	991	800	918	2,709
2039	999	801	936	2,735

Year	Residential	Commercial	Industrial	Total
2040	1,006	802	954	2,762
2041	1,013	803	972	2,789
2042	1,021	805	991	2,817
2043	1,028	806	1,010	2,845
2044	1,036	807	1,030	2,873
2045	1,043	809	1,050	2,902
2046	1,051	810	1,071	2,932
2047	1,059	811	1,091	2,961
2048	1,067	812	1,113	2,992
2049	1,075	814	1,134	3,022
2050	1,082	815	1,156	3,054
Average annual growth rate	0.5%	0.1%	3.0%	1.1%

Table 106. Econometric Net System Load with low growth conditions, MWa

Year	Residential	Commercial	Industrial	Total
2022	933	802	503	2,239
2023	918	812	559	2,289
2024	910	802	601	2,312
2025	902	792	634	2,329
2026	897	782	672	2,351
2027	895	771	703	2,369
2028	897	769	711	2,376
2029	901	768	713	2,382
2030	903	766	719	2,388
2031	906	764	724	2,395
2032	909	763	730	2,401

Year	Residential	Commercial	Industrial	Total
2033	912	761	736	2,408
2034	914	759	742	2,415
2035	917	758	748	2,423
2036	920	756	754	2,430
2037	923	754	760	2,438
2038	926	753	767	2,445
2039	929	751	773	2,453
2040	932	749	780	2,461
2041	935	748	787	2,470
2042	938	746	794	2,478
2043	941	744	802	2,487
2044	944	742	809	2,495
2045	947	741	817	2,504
2046	950	739	824	2,514
2047	953	737	832	2,523
2048	957	736	841	2,533
2049	960	734	849	2,543
2050	963	732	858	2,553
Average annual growth rate	0.1%	-0.3%	1.9%	0.5%

Table 107. Econometric Net System Load with high growth conditions, MWa

Year	Residential	Commercial	Industrial	Total
2022	926	813	628	2,367
2023	927	808	677	2,412
2024	931	803	731	2,464
2025	937	797	779	2,513

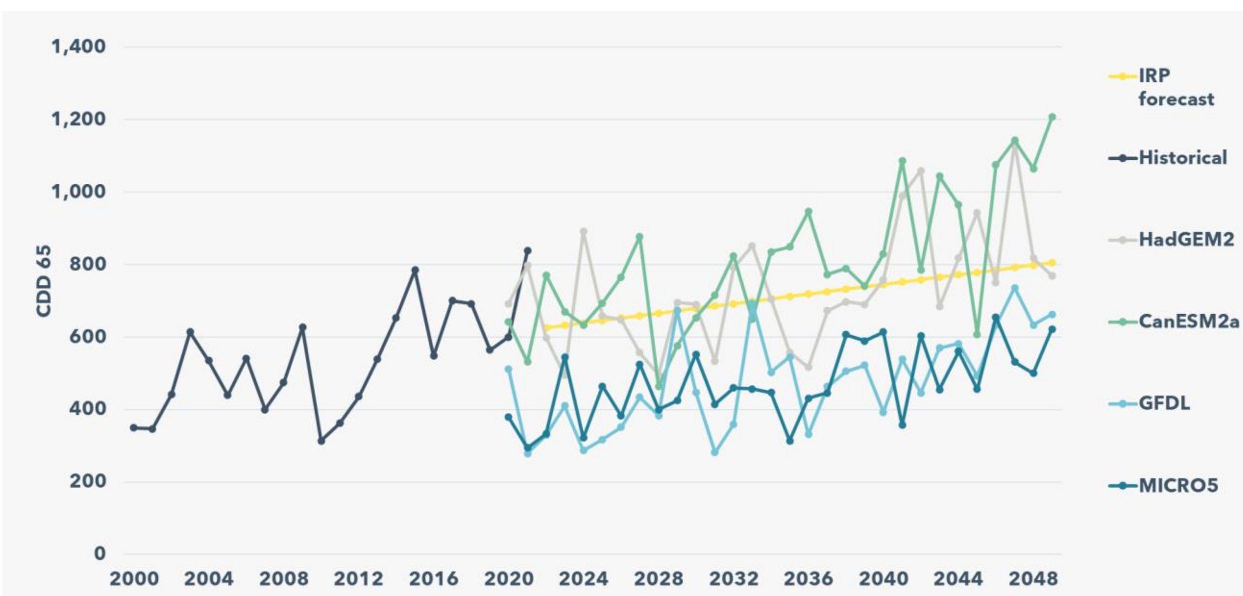
Year	Residential	Commercial	Industrial	Total
2026	947	800	804	2,552
2027	959	804	824	2,588
2028	971	808	848	2,626
2029	982	811	871	2,665
2030	994	815	895	2,703
2031	1,005	818	919	2,743
2032	1,017	822	944	2,782
2033	1,029	825	969	2,823
2034	1,040	829	994	2,863
2035	1,052	832	1,020	2,904
2036	1,064	836	1,046	2,946
2037	1,076	839	1,072	2,988
2038	1,089	843	1,099	3,031
2039	1,101	846	1,126	3,074
2040	1,113	850	1,154	3,117
2041	1,126	854	1,182	3,161
2042	1,138	857	1,210	3,205
2043	1,151	861	1,239	3,250
2044	1,164	864	1,268	3,296
2045	1,176	868	1,297	3,342
2046	1,189	871	1,327	3,388
2047	1,202	875	1,358	3,435
2048	1,216	879	1,388	3,482
2049	933	802	503	2,239
2050	926	817	572	2,316
Average annual growth rate	1.0%	0.3%	3.7%	1.6%

D.4 Climate change model data and the IRP load forecast

The temperature data used by the econometric load forecasting model have historical climate change trends built into them. In general, this increases cooling-degree days going forward and decreases heating-degree days.[443] The IRP compares these historical trends with climate model outputs to see how similar they are. The climate model data used in the comparison are from the River Management Joint Operating Committee (RMJOC) studies that use data from the Intergovernmental Panel on Climate Change (IPCC). The four models used in the comparison were selected by the RMJOC for streamflow analysis and were recommended for the IRP analysis by Creative Renewable Solutions.[444]

Figure 122 compares cooling degree days (CDD 65) annually between the historical data, the trend data used in the IRP econometric forecast, and the climate model outputs. Historical data and the econometric load forecast data are in gray. There is an upward trend in the econometric load forecast data. An upward trend in CDD 65 indicates warming temperatures in summer months and more demand for mechanical cooling (air conditioning). The figure data from the four climate models are in color and trend upwards, too.

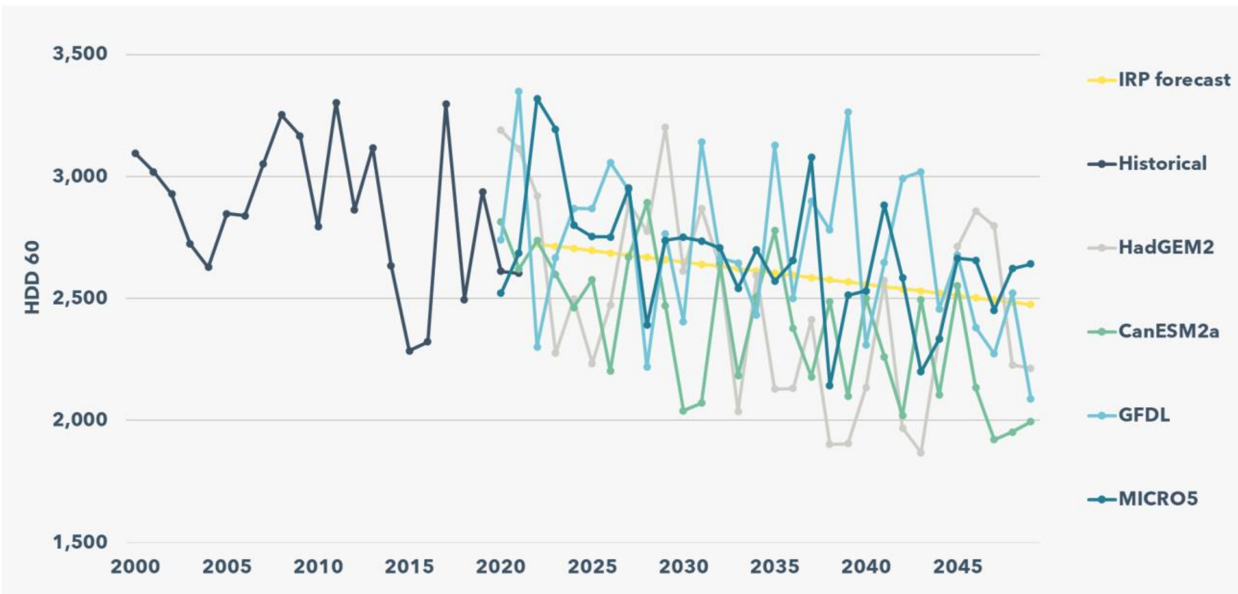
Figure 122. Annual cooling degree day forecasts



In **Figure 122**, the econometric load forecast CDD 65 inputs (in gray) trend inside the range of the climate change model data (in color). This indicates that the warming trend approach used by the econometric load forecasting model somewhat comports with the data from the climate change models.

Figure 123 compares heating degree days from historical data (in gray), the IRP econometric load forecast (in gray), and the climate change models (in color). All datasets show a decreasing trend in heating degree days on a yearly basis. This indicates warming temperatures in winter months, and a decreased need for heating.

Figure 123. Annual heating degree day forecasts



In **Figure 123**, the econometric load forecast HDD 65 inputs (in gray) trend inside the range of the climate change model data on an annual level. On a monthly level however, the econometric load forecast trend in December and February is flat, whereas the climate models have a declining trend (not shown).

Based on the observation that the annual HDD and CDD data used in the econometric load forecast are mostly in the range of the climate model data, PGE decided to stay with the warming trend approach for the 2023 IRP. In future planning work PGE will continue to update the trend approach while exploring using climate change model data.

443 Cooling degree days define days that average higher than a certain temperature, often 65 degrees F. An increase in cooling degree days indicates warming temperatures (and more need for air conditioning). Heating degree days define days that average less than a certain temperature, often 60 degrees F. A reduction in heating degree days indicates warming temperatures (and less need for heating).

444 Additional climate change data are available at: https://www.bpa.gov/energy-and-services/power/climate-change-fcrps