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Pacific Gas and Electric Company
2025 IEPR Electricity Demand Forms
Form 4 Demand Forecast Methods and Models
Prepared for the California Energy Commission

I. Demand and Price Forms (Historic and Forecast Electricity Demand)

Forms 1.1a-b Retail Sales of Electricity by Class or Sector (GWh)

PG&E is providing the requested market sector data in the historic period through November 2024. PG&E is presenting its sales data from a dedicated rate analytic database, which is continuously revised to account for rebates, rebills, and other types of billing irregularities. As such, the totals in this data set may not sync up identically with data provided in other forums (e.g., QFERs, Annual Power Report, etc.). Total retail sales are shown on Form 1.1a by customer class. The estimated consumption associated with Electric vehicles (EV) is shown as a separate column item although EV usage is actually embedded in customer class sales. Only system totals are available for recorded bundled sales data shown in Form 1.1b.

In the forecast period 2026-2036, PG&E has included the effects of energy efficiency as described in Section III Demand Forecast Methods below. PG&E has also included the impacts of EVs, building electrification, and distributed generation (DG), including rooftop solar (photovoltaic or PV). PG&E describes the methods it uses to produce these in Post-Regression Adjustments below.

In its forecast, PG&E also estimates loads associated with current and prospective community choice aggregation (CCA). A high-level discussion of PG&E's approach to CCA forecasting is provided in Section III of this document. PG&E does not assume reopening of direct access (DA) beyond the limited reopening mandated by SB 237.

PG&E is requesting confidential treatment for various portions of Form 1.1 as discussed in the Repeated Application for Confidentiality submitted with these forms.

Form 1.2 Distribution Area Net Electricity for Generation Load

DA and CCA load are provided in Form 1.2. The DA cap was unchanged from recent history. Losses include distribution, transmission, and unaccounted for energy for bundled, DA, and CCA customers (losses associated with BART loads are not included.) PG&E sales forecast is developed on a mitigated basis.

PG&E is requesting confidential treatment for various portions of Form 1.2 as discussed in the Repeated Application for Confidentiality submitted with these forms.

Form 1.3 LSE Coincident Peak Demand by Sector (Bundled Customers)

PG&E's peak demand forecast is not built up from sector-level data but is produced at the PG&E system level based on operational load data (see Demand Forecast Methods section for further details on the Peak Demand forecast process). For this reason, in Form 1.3, PG&E is only able to provide aggregate forecast data for bundled customer peaks. Bundled customer distribution losses are developed consistent with the distribution loss factor algorithms used in the Settlements process. Transmission losses and unaccounted for energy are assumed to be 2.5 percent and 0.5 percent, respectively, consistent with resource adequacy counting rules. As in Form 1.1 and 1.2, the effects of customer energy efficiency programs, incremental customer self-generation, EVs, new data centers, and electrification are included in the forecast data. In addition, the impacts of customer-owned storage and historically expected demand response are included in the peak forecast data.

Form 1.4 Distribution Area Coincident Peak Demand

Losses are assumed to be 3 percent for transmission and unaccounted for energy. All assumptions are the same as described in Form 1.3 above. Annual system-coincident peak demand of load components may not equal the max of monthly system-coincident peak demand reported elsewhere.

Form 1.5 Peak Demand Weather Scenarios

Forecast data are provided for each of the temperature scenarios requested. Scenario forecasts are produced by simulating the peak demand forecast model over varying assumptions of peak temperature conditions. All assumptions are the same as described in Form 1.3 above.

PG&E is requesting confidential treatment for various portions of Form 1.5 as discussed in the Repeated Application for Confidentiality submitted with these forms.

Form 1.6a Recorded LSE hourly loads for 2023, 2024 and Forecast Loads for 2025

Certain load may be served by both wholesale and retail purchases. The wholesale portion of this load is shown in the column entitled "Other Load (Wholesale)." The retail load portion of this load is reflected in the bundled load column.

Total system load includes bundled and unbundled load, bundled and unbundled losses, and other load (wholesale).

Historical distribution losses for 2023 and 2024 are consistent with the distribution loss factor algorithms used in the Settlements process. Forecasted distribution losses for 2025 are based upon the same distribution loss factor algorithms mentioned above.

Transmission losses and unaccounted for energy for historical and forecasted load are assumed to be 2.5% and 0.5%, respectively, consistent with resource adequacy counting rules.

PG&E is requesting confidential treatment for various portions of Form 1.6a as discussed in the Repeated Application for Confidentiality submitted with these forms.

II. Forecast Input Assumptions

Form 2.1 PG&E Planning Area Economic and Demographic Inputs

Inputs are drawn from Moody's Analytics December 2024 baseline projections for PG&E's service area economy.

Form 2.2 Electricity Rate Forecast

PG&E reviewed and updated the 2024 regression models for the class accounts and load forecasts. The residential rate variable used in some previous residential load forecasts was statistically insignificant and therefore did not contribute to explaining the usage of residential customers. Its contribution to explaining the usage of residential customers was best left to more significant drivers and removed from the model. The commercial rate variable previously used in the commercial regression was tested as marginally significant and also removed from the model. With the exception of agriculture, the 2025 load forecast models did not contain rate variables and therefore the non-agricultural columns in Form 2.2 in the 2025 IEPR filing are blank. Forward-looking revenue requirements will be included in Forms 8.1a and 8.1b.

The general treatment of rate variables in the agricultural forecast is determined by the AG Parties Settlement in 2021, PG&E included an agriculture rate variable in both the sales and the accounts regression models. In both models, the variable was significant. The rate variable with a positive coefficient negatively influences sales.

Form 2.3 Customer Count & Other Forecasting Inputs

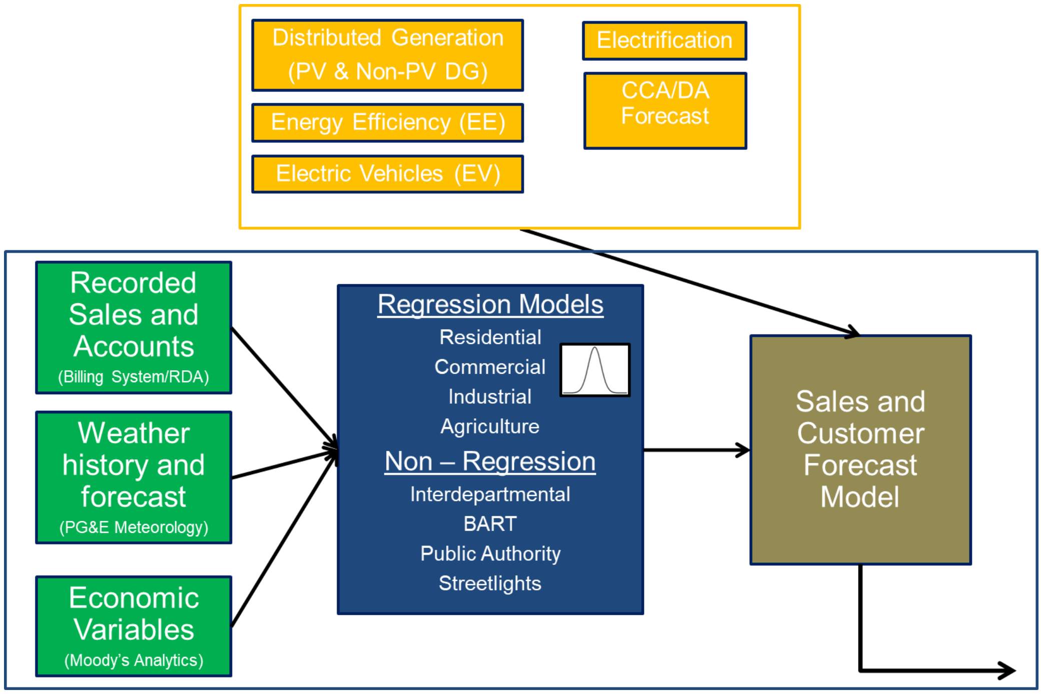
Form 2.3 provides recorded and projected customer counts by customer class. The data reported is billing data (number of bills), which is used to represent the number of customers. The annual numbers reported are averages of 12 months of customer data.

III. Demand Forecast Methods

PG&E uses an econometric approach with time series data to develop its electricity consumption (energy) forecast. Post-regression adjustments are then made to capture the future effects of distributed generation, energy efficiency, EVs, building electrification, new large data centers, battery storage, and community choice aggregation. PG&E's process for developing forecasts of energy sales is shown in Figure 1.

PG&E's peak demand (peak) forecast presented in Forms 1.3 and 1.4 is developed by shaping the monthly energy forecast to an hourly level and adjusting the load shape to incorporate the effects of Distributed Energy Resources (DERs) on system load, particularly behind-the-meter solar PV, EV charging and behind-the-meter storage charging/discharging.

Figure 1: Electricity Sales Forecast Process Map



PG&E develops its energy forecast by major customer class for the retail system, which includes sales to both bundled customers and non-utility procurement customers (e.g., Community Choice Aggregation (CCA), Direct Access (DA), and BART).

The major customer classes for which PG&E uses an energy forecast to set rates are:

- Residential: Single family residences and separately billed units in multi-family structures.
- Small Commercial: Commercial business < 200 kW
- Medium Commercial: Commercial business < 500 kW
- Large Commercial & Industrial: Commercial business > 499 kW; Commercial / Industrial customer > 999 kW
- Agricultural: End use agricultural products + a few agricultural processing customers

The above customer classes account for about 98 percent of PG&E's annual electric usage. The remaining customers, BART, public authority, street lighting, and interdepartmental, account for the remainder. Municipal utility districts (e.g., Palo Alto, Alameda) and irrigation districts (e.g., Modesto, Merced) are excluded from PG&E's forecast of sales and peak, which is concerned solely with retail customer usage. Note also that PG&E forecasts peak demand at the retail area, not the Transmission Access Charge or TAC area. PG&E's retail area does not include Department of Water Resources, BART, Western Area Power Authority, or any municipally served territories.

PG&E constructs regression models with variables that drive the demand for electricity: economics/demographics, and weather, plus time series terms to assure no autocorrelation in the residuals. PG&E favors variables that are statistically significant predictors of energy demand; however, PG&E does not make that an absolute requirement so long as a variable is conceptually sound. The specific inputs vary from model to model and are shown in greater detail below. Moody's Analytics provides economic and demographic history and forecasts. Weather inputs are drawn from PG&E's meteorological services and a National Center on Atmospheric Research (NCAR) study on future normal weather in PG&E service territory with climate change impacts.

Due to the AG Parties Settlement, PG&E included the Palmer Drought Severity Index (PDSI), an agriculture rate value, a measure of agriculture output in California which is from the United States Department of Agriculture (USDA) Economic Research Service (ERS) historical statewide Net Cash Income. The Palmer Drought Severity Index is obtained from the National Oceanic and Atmospheric Administration. The PDSI is calculated based on precipitation and temperature data, as well as the local Available Water Content (AWC) of the soil.

PG&E models COVID impacts by class using 5 dummy variables that cover the historical months of COVID from 2020 and thru 2024. One dummy variable runs from March 2020 through December 2020, the second dummy variable covers 2021, the third covers 2022, the fourth 2023 and the fifth 2024. This is a simplified model intended to capture the effect of the COVID pandemic on sales for Residential and Commercial classes.

Model Components

Equations for the four major customer class energy forecasts are shown below (pp. 7-15):

Residential Accounts

Residential Accounts

Dependent Variable: D(RES_ACCTS_IDA)				
Method: ARMA Conditional Least Squares (BFGS / Marquardt steps)				
Date: 01/28/25 Time: 15:35				
Sample: 2005M01 2024M11				
Included observations: 239				
Convergence achieved after 6 iterations				
Coefficient covariance computed using outer product of gradients				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
SINGLE_FAMILY_PERMITS	0.0588	0.0137	4.2950	0
JAN	-898.8671	1045.7410	-0.8596	0.3909
FEB	474.7490	1014.6950	0.4679	0.6403
MAR	3285.0710	1019.4760	3.2223	0.0015
APR	1365.0750	1015.2510	1.3446	0.1801
MAY	4327.8820	1013.5220	4.2701	0
JUN	6991.3390	1011.7710	6.9100	0
JUL	3135.4200	1010.1550	3.1039	0.0022
AUG	5661.8820	1008.8780	5.6121	0
SEP	-5312.7010	1010.5430	-5.2573	0
OCT	-5368.1070	1005.6140	-5.3381	0
NOV	-2963.9500	1029.1540	-2.8800	0.0044
AR(1)	-0.1979	0.0652	-3.0342	0.0027
R-squared	0.5075	Mean dependent var		2578.247
Adjusted R-squared	0.481331	S.D. dependent var		5695.255
S.E. of regression	4101.646	Akaike info criterion		19.52902
Sum squared resid	3.80E+09	Schwarz criterion		19.71812
Log likelihood	-2.32E+03	Hannan-Quinn criter.		19.60522
Durbin-Watson stat	1.996339			

SINGLE_FAM_PERMS_PGE = Single family house permits

JAN, FEB, MAR, APRAPR, MAY, JUN, JUL, AUG, SEP, OCT, NOV = Monthly Dummies

Residential Usage per Account

Residential Usage				
Dependent Variable: LOG(RES_SALES_IDA_EXPLICIT				
/RES_ACCTS_FORE_NOV)				
Method: ARMA Conditional Least Squares (BFGS / Marquardt steps)				
Date: 02/07/25 Time: 10:30				
Sample: 2005M01 2024M11				
Included observations: 239				
Convergence achieved after 35 iterations				
Coefficient covariance computed using outer product of gradients				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.0833	0.0393	154.6629	0
CDD	0.0022	0.0001	21.7738	0
HDD	0.0005	0.0000	12.1783	0
COVID_POST_MARCH2020	0.0916	0.0133	6.9042	0
COVID_CALENDAR2021	0.0574	0.0172	3.3355	0.001
COVID_CALENDAR2022	0.0276	0.0222	1.243691	0.2149
COVID_CALENDAR2023	0.0269	0.025952	1.035631	0.3015
COVID_CALENDAR2024	0.0154	0.029607	0.52082	0.6030
AR(1)	0.4277	0.061147	6.995186	0.0000
SAR(12)	0.8930	0.034969	25.53558	0.0000
R-squared	0.9585	Mean dependent var		6.3064
Adjusted R-squared	0.9569	S.D. dependent var		0.1289
S.E. of regression	0.026771	Akaike info criterion		-4.36206
Sum squared resid	0.16412	Schwarz criterion		-4.2166
Log likelihood	531.2662	Hannan-Quinn criter.		-4.30344
F-statistic	587.8797	Durbin-Watson stat		1.916657
Prob(F-statistic)	0			

HDD = Heating Degree Days (PG&E Territory)

CDD = Cooling Degree Days (PG&E Territory)

COVID_POST_MARCH2020 - Covid Dummy Variable for Mar - Dec 2020
COVID_CALENDAR2021- Covid Dummy Variable for 2021
COVID_CALENDAR2022- Covid Dummy Variable for 2022
COVID_CALENDAR2023- Covid Dummy Variable for 2023
COVID_CALENDAR2024- Covid Dummy Variable for 2024

Commercial Accounts

Commerical Accounts				
Dependent Variable: D(COM_ACCTS_IDA)				
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)				
Date: 02/07/25 Time: 10:33				
Sample: 2005M01 2024M12				
Included observations: 240				
Convergence achieved after 5 iterations				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-40.84182	43.71231	-0.934332	0.3511
D(RES_ACCTS_FORE_WOPPH)	0.0563	0.0065	8.7023	0
Apr-13	-3179.3720	583.0035	-5.4534	0
May-13	3235.3030	582.7819	5.5515	0
AR(1)	0.0719	0.0709	1.0147	0.3113
R-squared	0.3736	Mean dependent var		100.3792
Adjusted R-squared	0.3630	S.D. dependent var		728.6733
S.E. of regression	581.5768	Akaike info criterion		15.58998
Sum squared resid	79484407.0000	Schwarz criterion		15.66249
Log likelihood	-1866	Hannan-Quinn criter.		15.61919
F-statistic	35.0471	Durbin-Watson stat		1.857861
Prob(F-statistic)	0			

C = Constant
RES_ACCTS_FORE_WOPPH - Residential Accounts Forecast
Apr-2013 = Month dummy to clean regression results for outlier data point.
May-2013 = Month dummy to clean regression results for outlier data point.

Commercial Usage per Account

Commercial Usage				
Dependent Variable: LOG(COM_SALES_IDA_EXPLICIT /COM_ACCTS_FORE_FINAL)				
Method: ARMA Conditional Least Squares (Gauss-Newton / Marquardt steps)				
Date: 02/07/25 Time: 10:31				
Sample: 2005M01 2024M11				
Included observations: 239				
Convergence achieved after 15 iterations				
Coefficient covariance computed using outer product of gradients				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.1314	0.1218	66.7339	0.0000
LOG(EMP_COMM_SECTOR_PGE)	-0.5590	0.1857	-3.0107	0.0029
CDD	0.0010	0.0001	14.9874	0.0000
COVID_POST_MARCH2020	-0.1169	0.0115	-10.1696	0.0000
COVID_CALENDAR2021	-0.0868	0.0129	-6.7263	0.0000
COVID_CALENDAR2022	-0.0527	0.0153	-3.4384	0.0007
COVID_CALENDAR2023	-0.0450	0.0167	-2.6962	0.0075
COVID_CALENDAR2024	-0.0508	0.0180	-2.8153	0.0053
AR(1)	0.5347	0.0581	9.1988	0.0000
SAR(12)	0.6253	0.0543	11.5161	0.0000
R-squared	0.9516	Mean dependent var		8.5253
Adjusted R-squared	0.9497	S.D. dependent var		0.0854
S.E. of regression	0.0192	Akaike info criterion		-5.0310
Sum squared resid	0.0841	Schwarz criterion		-4.8855
Log likelihood	611.2003	Hannan-Quinn criter.		-4.9723
F-statistic	499.9401	Durbin-Watson stat		2.0522
Prob(F-statistic)	0.0000			

C = Constant
EMP_INFO = Employment in information services (PG&E Territory)
EMP_FIN = Employment in financial services (PG&E Territory)
EMP_TOT_SVC = Total services employment (PG&E Territory)
EMP_TOT_PGE = Total employment (PG&E Territory)
EMP_COMM_SECTOR_PGE = (EMP_INFO + EMP_FIN + EMP_TOT_SVC)/EMP_TOT_PGE
CDD = Cooling Degree Days (PG&E Territory)
COVID_POST_MARCH2020 - Covid Dummy Variable for Mar - Dec 2020
COVID_CALENDAR2021- Covid Dummy Variable for 2021
COVID_CALENDAR2022- Covid Dummy Variable for 2022

COVID_CALENDAR2023- Covid Dummy Variable for 2023
COVID_CALENDAR2024- Covid Dummy Variable for 2024

Industrial Sales per Account

Industrial Usage				
Dependent Variable: LOG(IND_SALES_RDA_EXPLICIT/IND_ACCTS_FORE _NOV)				
Method: ARMA Conditional Least Squares (Gauss-Newton / Marquardt steps)				
Date: 02/07/25 Time: 10:34				
Sample: 2005M01 2024M11				
Included observations: 239				
Convergence achieved after 6 iterations				
Coefficient covariance computed using outer product of gradients				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.056E+01	0.3917	26.9688	0
LOG(GDP_MANUFACTURING)	2.793E-01	0.0334	8.3712	0
CDD	3.440E-04	0.0001	3.0526	0.0025
JAN	9.728E-03	0.0060	1.6142	0.1079
FEB	4.090E-03	0.0079	0.5148	0.6072
MAR	5.802E-02	0.0091	6.3954	0
APR	6.269E-02	0.0098	6.3757	0
MAY	6.770E-02	0.0110	6.1286	0
JUN	6.688E-02	0.0145	4.6157	0
JUL	9.237E-02	0.0189	4.8998	0
AUG	1.156E-01	0.0180	6.4102	0
SEP	1.152E-01	0.0136	8.4640	0
OCT	8.449E-02	0.0088	9.5801	0
NOV	4.368E-02	0.0062	7.0941	0
AR(1)	7.610E-01	0.0432	17.6041	0
R-squared	0.9214	Mean dependent var		13.91345
Adjusted R-squared	0.9164	S.D. dependent var		0.0878
S.E. of regression	0.0254	Akaike info criterion		-4.4479
Sum squared resid	0.1445	Schwarz criterion		-4.2297
Log likelihood	546.5189	Hannan-Quinn criter.		-4.3599
F-statistic	187.4365	Durbin-Watson stat		2.2350
Prob(F-statistic)	0			

GDP_MANUFACTURING_PGE = Gross product of manufacturing (PG&E Territory)
CDD = Cooling Degree Days (PG&E Territory)
JAN, FEB, MAR, APR, MAY, JUN, JUL, AUG, SEP, OCT, NOV = Monthly dummies

Industrial Accounts

Industrial Accounts are forecast using a straight line of the last observation.

Agriculture Accounts and Sales

Agricultural Accounts				
Dependent Variable: LOG(AG_ACCTS_IDA)				
Method: Least Squares				
Date: 02/07/25 Time: 10:38				
Sample: 2005M01 2024M11				
Included observations: 239				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	11.35268	0.027264	416.3973	0
JAN	0.0	0.0066	-0.9322	0.3522
FEB	-0.0063	0.0066	-0.9543	0.3409
MAR	-0.0036	0.0066	-0.5497	0.5831
APR	-0.0003	0.0066	-0.0421	0.9665
MAY	0.0038	0.0066	0.5771	0.5645
JUN	0.0055	0.0066	0.8347	0.4048
JUL	0.0062	0.0066	0.9451	0.3456
AUG	0.0063	0.0066	0.9532	0.3415
SEP	0.0050	0.006599	0.759063	0.4486
OCT	0.0032	0.006598	0.480008	0.6317
NOV	-0.0004	0.0066	-0.053576	0.9573
PDSI_2025	-0.0005	0.000549	-0.823143	0.4113
PDSI_LAGGED_2025	-0.0025	0.00055	-4.50161	0
AG_VA_USDA_TWOPERCENTGROWTH	0.0000	4.32E-10	13.5725	0
LOG(ESCALATED_RATE_CWMA)	0.0821	0.011461	7.163863	0
R-squared	0.797876	Mean dependent var		11.3631
Adjusted R-squared	0.78428	S.D. dependent var		0.044319
S.E. of regression	0.020584	Akaike info criterion		-4.864
Sum squared resid	0.094486	Schwarz criterion		-4.63127
Log likelihood	597.2483	Hannan-Quinn criter.		-4.77022
F-statistic	58.68542	Durbin-Watson stat		0.085749
Prob(F-statistic)	0			

C = Constant

AG_VA_USDA_TWOPERCENTGROWTH = United States Department of Agriculture (USDA) Economic Research Service (ERS) historical statewide Net Cash Income (Thousands Current$)

JAN, FEB, MAR, APR, MAY, JUN, JUL, AUG, SEP, OCT, NOV = Monthly dummies

PDSI_2025 = The Palmer Drought Severity Index (PDSI) uses readily available temperature and precipitation data to estimate relative dryness

PDSI_LAGGED_2025 = The Palmer Drought Severity Index (PDSI) Averaged and Lagged by a year.

ESCALATED_RATE_CWMA = Centrally weighted moving average of the PGE Agriculture rate.

Agricultural Sales				
Dependent Variable: LOG(AG_SALES_IDA_EXPLICIT)				
Method: Least Squares				
Date: 02/07/25 Time: 10:39				
Sample: 2005M01 2024M11				
Included observations: 239				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	18.16473	0.1420	127.8886	0
JAN	-0.043925	0.0344	-1.276415	0.2031
FEB	0.109892	0.0344	3.194149	0.0016
MAR	0.30489	0.0344	8.86624	0
APR	0.633049	0.0344	18.41938	0
MAY	0.970883	0.0344	28.24856	0
JUN	1.17455	0.0344	34.17776	0
JUL	1.26313	0.0344	36.75951	0
AUG	1.172738	0.0344	34.12541	0
SEP	0.944603	0.0344	27.47601	0
OCT	0.694828	0.0344	20.21501	0
NOV	0.342701	0.0344	9.967091	0
PDSI_2025	-0.045171	0.0029	-15.78886	0
PDSI_LAGGED_2025	-0.012739	0.0029	-4.447844	0
AG_VA_USDA_TWOPERCENTGROWTH	3.06E-08	0.0000	13.58401	0
LOG(ESCALATED_RATE_CWMA)	-0.180436	0.0597	-3.022122	0.0028
R-squared	0.960717	Mean dependent var		19.9301
Adjusted R-squared	0.958075	S.D. dependent var		0.523722
S.E. of regression	0.107235	Akaike info criterion		-1.56299
Sum squared resid	2.5644	Schwarz criterion		-1.33025
Log likelihood	202.7769	Hannan-Quinn criter.		-1.4692
F-statistic	3.636E+02	Durbin-Watson stat		0.860234
Prob(F-statistic)	0.000E+00			

C = Constant

AG_VA_USDA_TWOPERCENTGROWTH = United States Department of Agriculture (USDA) Economic Research Service (ERS) historical statewide Net Cash Income (Thousands Current$)

JAN, FEB, MAR, APR, MAY, JUN, JUL, AUG, SEP, OCT, NOV = Monthly dummies

PDSI_2025 = The Palmer Drought Severity Index (PDSI) uses readily available temperature and precipitation data to estimate relative dryness

PDSI_LAGGED_2025 = The Palmer Drought Severity Index (PDSI) averaged and lagged by a year.

ESCALATED_RATE_CWMA = Centrally weighted moving average of the PGE agriculture rate.

<u>Post-Regression Adjustments</u>

Expectations of future increases in sales loss to energy efficiency and distributed generation as well as sales gain due to electric vehicles and building electrification are also incorporated into the forecast. For most of these policies, PG&E's approach is to compare the level of the impact in the existing data with the levels that are anticipated in the future, and to adjust the forecast accordingly. The forecasted levels for these load modifying resources are derived using forecasting methods explained in detail immediately below.

Load Modifier Forecast Methodologies

1. Battery Energy Storage Forecast Methodology

a. Scope

For the purposes of forecasting behind the meter (BTM) energy storage adoption and capacity (MW) impacts, PG&E assumes that all energy storage is lithium ion and generates value by arbitraging customer retail rates (e.g., volumetric energy and demand charges) based on a set of representative rates and load shapes. PG&E estimates the impact of BTM storage to the energy (GWh) forecast (due to round-trip-efficiency losses) by summing all storage charging and discharging values within each calendar year. The model used for this forecast is deterministic in nature.

b. Forecast Method Overview

The model for customer adoption (installed MW capacity) has multiple steps. The first part consisting of a model that optimizes the behavior for BTM storage under different load shapes and rates. The second step estimates the value to customers operating storage under these optimal conditions. The third step projects adoption over the forecast time horizon using a Bass technology diffusion model.

c. Forecast Method Details

i. Dispatch Optimization

Storage is dispatched to minimize monthly customer bills and is constrained by the battery's assumed technical characteristics. The minimized components of the objective function are the avoidable components of the customer's bill plus the costs of battery degradation and O&M. These include the aggregated demand charges incurred by the customer and the aggregated energy charges.

ii. Storage Adoption

The second component of the model estimates the adoption of storage over time based on the benefits to the customer versus the cost of the technology. At a high level, adoption is calculated through the following steps:

- Estimate current storage adoption using PG&E interconnection data.
- Determine addressable market for each customer class based on property ownership assumptions.
- Determine market potential for each customer class based on their benefit and cost ratios and market share curves. This is divided between customers with PV on the roof and customers without PV, since PV changes the benefit-cost ratio of storage. Adoptions of rooftop PV are a fixed trajectory input (from PG&E's BTM Solar forecast) in the model, so the only adoption decision being made by the customer is whether to adopt storage or not. The storage tool therefore does not explicitly simulate the adoptions of BTM PV + storage systems as a combined package. Instead, the tool assumes customers only install a PV + storage system when they own a PV system already.
- Determine the adoption over time using a Bass technology diffusion approach and assumed storage attachment rates. The Bass diffusion modeling approach is described in further detail in the BTM Solar Forecast Methodology (section 2 of this form). The inputs and assumptions used for the BTM storage model are consistent with the BTM solar model.

iii. Storage Peak Impact

To estimate the aggregated load-shift impact from residential BTM storage, PG&E uses load shapes based on CEC's 2021 IEPR BTM storage forecast. PG&E assumes that residential customers will use 70% of their storage energy capacity for load shifting. Until 2030, PG&E assumes storage discharge follows a relatively flat shape for HE17-24, and a more dynamic shape (following CEC 2021 IEPR forecast) for years 2030 onward.

To estimate the aggregated load-shift impact from non-residential BTM storage, the dispatch profiles from the optimization model are scaled up based on the projected installed MWs for each modeled customer segment. The segment profiles are then aggregated, and the charge/discharge hours are smoothed over blocks of like-hours within rate schedule time periods to reflect the heterogeneity amongst customer load shapes.

d. Key Inputs and Assumptions

- **Customer profiles** – Twelve representative profiles were selected based on a clustering analysis of historical load profiles that was completed in prior years. The profiles covered the Residential, Small Commercial & Industrial, Medium Commercial & Industrial, Large Commercial & Industrial, and Agricultural segments. These profiles are considered representative of the broader population.

- **Retail rates** – Storage-friendly rates such as E-ELEC for Residential and Option S for Commercial & Industrial were used to estimate bill savings. PG&E assumed no enrollment caps for the rates. Assumptions about rate structures in future years were informed by discussions with internal subject matter experts.
- **NEM policy** – The model assumes the Net Billing Tariff policy.
- **Technology costs** – The model considers only lithium-ion battery technologies. Estimated lithium-ion storage system costs are based on internal and external market analyst projections.[1]
- **Operational characteristic** – The model assumes operational controls exist for customers to optimize storage units to minimize their bill. In addition, the model assumes storage system operators have perfect foresight into future loads and future PV generation (if PV paired). Lastly, no multiple use applications are accounted for.
- **Policy/Regulatory drivers** – No programmatic procurement targets are included in the forecast. Primary financial incentives are the Investment Tax Credit, which includes the phase-down schedule as of 2024, and the Self-Generation Incentive Program, where PG&E assumes a phase-down and phase-out by 2026.
- **Residential storage attachment rate** – Residential storage attachment rates (i.e., co-adoption of PV and storage) are estimated based on internal interconnection data and subject matter expert consultation.

2. Behind-the-Meter Solar Forecast Methodology

a. Scope

In Form 3, PG&E provides its installed capacity (MW), estimated energy generation (MWh) and coincident peak impact (MW) for behind-the-meter (BTM) solar photovoltaic (PV) within its service territory. In this form (Form 4), PG&E provides an overview of the methods, inputs, and assumptions used to develop its forecast of BTM solar PV. The programs covered as part of this forecast include: the Net Billing Tariff (and their successor tariffs), the Climate Innovation Program (AB 209), On-Bill Financing (through PG&E), Title 24 (codes and standards for residential buildings), and low-income solar programs (i.e., DAC-SASH, and SOMAH).

b. Forecast Method Overview

PG&E projects customer adoption of BTM solar and estimates generation associated with historical and forecasted installed capacities. Historical installed BTM PV capacity is obtained internally and updated each year. To forecast PV adoption, PG&E uses two separate approaches: (1) a Bass Diffusion[2] modeling framework is

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[1] The following analyst reports and forecasts were considered:

a) NREL (National Renewable Energy Laboratory). 2024. 2024 Annual Technology Baseline. Golden, CO: National Renewable Energy Laboratory.

[2] Bass, F. 1969, Bass, F. 1969, "A new product growth model for consumer durables, A new product growth model for consumer durables," Management Science, Management Science, Vol. 15, no. 4, pp. 215-227

applied to the mass market retrofit adoptions, and (2) a policy goals model is applied to new residential construction and low-income markets. The Bass Diffusion model forecasts new PV adoptions based on customers' economic decision-making given different cost-effectiveness and technical constraints. In addition to forecasting economically driven customer PV adoption using the Bass diffusion model, PG&E forecasts adoption driven by policy mandates such as Zero Net Energy (ZNE) goals, and low-income programs based on program rules and, where appropriate, program funding and forecasted costs of solar PV. An hourly capacity factor, an average of many capacity factors across several locations in PG&E service territory weighted by installed BTM PV capacity, is then applied to the installed capacity to estimate hourly generation.

c. *Forecast Method Details*

i. Mass Market Retrofit Forecast Approach

PG&E uses Bass Diffusion to forecast adoption in the mass market retrofit segment. Adoption of new BTM solar PV is forecasted by assessing market size and modeling how a technology is likely to spread within that market. In the modeling framework used by PG&E, adoption, *n(t),* is a function of:

- The "market potential," $\overline{Nt}$, or the pool of customers who can adopt in a given year, (*t)*
- The level of adoption that has already occurred as of the preceding time period (N_{t-1})
- Parameters that determine the rate of adoption within the market potential:
  - The diffusion parameter (*p)* commonly referred to as the "coefficient of innovation" or the "advertising effect" and captures the effect of advertising or the technology's inherent attractiveness to customers
  - The parameter (*q)* commonly referred to as the "coefficient of imitation" or the "word-of-mouth effect" and is designed to capture increasing levels of consumer confidence and interest in a technology as the technology is more widely adopted

Discretized Bass Diffusion Model: $n(t) \; = \; \left[p + \frac{q}{N(t)} N_{t-1}\right]\left[\overline{N_t} - N_{t-1}\right]$

PG&E estimates the market potential for BTM solar in a given year by customer sector and models the rate of diffusion within that sector using diffusion parameters (p and q) that are calibrated to historical adoption and benchmarked to available literature.[3] In a given year, market potential is estimated by first identifying the fraction of all customers with the capacity to adopt, meaning that they are not constrained from adopting by technical barriers such as a lack of suitable roof space or by other market

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[3] a) Sultan, Farley, and Lehmann (1990), "A Meta-Analysis of Applications of Diffusion Models." *J. Marketing Research* 27(1). https://www0.gsb.columbia.edu/mygsb/faculty/research/pubfiles/909/909.pdf

b)Van den Bulte and Stremersch (2004), "Social Contagion and Income Heterogeneity in New Product Diffusion: A Meta-Analytic Test." *Marketing Science* 23(4).

c) Meade and Islam (2006), "Modelling and forecasting the diffusion of innovation – A 25-year review." *International Journal of Forecasting* 22.

barriers such as property ownership. This set of customers is identified in PG&E's modeling framework as the "addressable market."

For customers in the addressable market, PV cost-effectiveness is estimated based on forecasted solar costs and bill savings. The portion of the addressable market that would be willing to adopt at a given level of cost-effectiveness is defined by a "market share curve."[4] This curve estimates customer demand for BTM solar at varying levels of cost-effectiveness. The market potential in a given year is the subset of customers within the addressable market for whom PV is a cost-effective investment decision. The following sections further describe these components in PG&E's PV adoption modeling framework.

Estimating the Addressable Market

The addressable market of customers who can adopt in a given year is estimated by accounting for factors that are likely to constrain customers' ability to adopt, including access to space for PV (technical potential), owner-occupancy, and transaction costs relative to potential savings (higher transaction costs relative to potential savings is likely to constrain adoption among lower usage customers).

Estimating Cost-Effectiveness

The cost-effectiveness of BTM solar is estimated based on forecasted solar costs compared to bill savings under Net Billing Tariff. The costs of BTM solar are estimated based on market analyst projections.[5] Bill savings are then estimated using rates and TOU periods representing each customer segment in PG&E's service territory.

Estimating a Market Share Curve

The relationship between cost-effectiveness and demand for solar was modeled based on a survey of potential and actual solar adopters conducted in 2013 by the US National Renewable Energy Lab. In that study, researchers evaluated the fraction of customers who would be willing to adopt at varying levels of bill savings.[6]

ii. Solar Mandates and Low-Income Programs

In addition to customer-driven adoption modeled using Bass Diffusion, PG&E models PV adoption associated with requirements for solar on new residential

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[4] Sigrin, B, and Drury, E., 2014. Diffusion into New Markets: Economic Returns Required by Households to Adopt Rooftop Photovoltaics http://www.aaai.org/ocs/index.php/FSS/FSS14/paper/view/9222

[5] The following analyst reports and forecasts were considered:

a) NREL (National Renewable Energy Laboratory). 2024. 2024 Annual Technology Baseline. Golden, CO: National Renewable Energy Laboratory.

b) IHS Global Insights: US Solar PV Capital Cost and LCOE Outlook. Published December 2019; cost per Watt through 2050

c) Bloomberg New Energy Finance (BNEF): 2H 2022 U.S. Clean Energy Market Outlook. Published October 2022; cost per Watt through 2030.

d) GTM Research: us-solar-pv-system-pricing-h1-2020. Published June 2020

[6] Sigrin, B, and Drury, E., 2014. Diffusion into New Markets: Economic Returns Required by Households to Adopt Rooftop Photovoltaics http://www.aaai.org/ocs/index.php/FSS/FSS14/paper/view/9222

construction, as well PV adoption driven by incentive programs for low-income customers.

Solar PV from New Construction

PG&E forecasts BTM PV on new homes per California's Zero Net Energy goals. Requirements for solar on new residential construction were established through the 2022 Title 24 update, with some limited exemptions. For solar on new residential construction, PG&E forecasts the share of new homes anticipated to install BTM solar PV as a result of Title 24 ZNE requirements and to the new housing start projections for PG&E's service area developed by Moody's analytics. PG&E uses the recommended PV system size for single and multifamily homes to forecast new installed capacity for new homes complying with Title 24.[7]

Solar PV from Low Income Programs

PG&E's forecast includes PV installations associated with low-income programs over the forecast horizon. Installations are estimated based on funding levels associated with the Disadvantaged Communities - Single-Family Solar Homes program (DAC-SASH), and Solar on Multi-Family Affordable Housing (SOMAH), which established funding for solar in disadvantaged communities.[8,9] The annual forecast is produced by distributing the remaining installed capacity of each program across the number of years left in the program.

Solar PV from Other Programs

PG&E's forecast also includes PV installations associated with anticipated funding through California's Climate Innovation Program (AB 209)[10] and internal assessments of customers eligible for energy efficiency upgrades through PG&E's On-Bill Financing Program. Installations are based on estimated funding levels and are distributed annually across the duration of each program.

iii. System Retirements

The last step in the installed capacity portion of the BTM PV forecast includes incorporating system retirements. The BTM PV forecast assumes PV system lifetimes extend 30 years[11], after which the system is retired.

iv. Energy from Installed Capacity

Once the installed capacity forecast is completed, an annual degradation rate of 0.5%[12] is applied to account for system degradation over time. An hourly capacity factor

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[7] 2022 Energy Code Update Rulemaking. 15-Day Express Terms 2022 Energy Code - Residential and Nonresidential. California Energy Commission. Submitted 7/14/2021.https://efiling.energy.ca.gov/GetDocument.aspx?tn=238848&DocumentContentId=72256

[8] https://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M313/K697/313697139.PDF

[9] http://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M158/K181/158181678.pdf

[10] https://www.energy.ca.gov/event/workshop/2023-11/climate-innovation-program-update-workshop

[11] PG&E internal analysis

[12] PG&E internal analysis

is used to convert installed capacity to hourly generation throughout the forecast time horizon.

d. Key Inputs and Assumptions

Key drivers and assumptions not described in the preceding section are outlined below.

- Customer Profiles Assumptions:
  - The customer market share reflects a customer's responsiveness to the value proposition offered by rooftop solar
  - Addressable market constrains overall adoption
- Retail Rate Assumptions:
  - PG&E assumes that retail electricity rates continue to escalate
- Technology Cost Assumptions:
  - PG&E assumes technology costs continue to decline but that vendor pricing strategies may not fully reflect cost declines in retail prices
  - PG&E assumes that the ITC ramp-down goes forward as planned
- Operational Assumptions:
  - PG&E assumes solar is non-dispatchable; interactions with BTM storage are modeled separately in the storage forecast
- Policy/Regulatory Drivers (e.g., NEM, ITC)
  - NEM reform (and successor programs) could decrease compensation for exported energy
  - Retail rate escalation could increase the value proposition for customers
  - Programmatic funding levels are consistent with current legislation

3. Building Electrification Forecast Methodology

a. Scope

For Building Electrification (BE), PG&E forecasts the conversion of natural gas appliances to electric appliances in the residential and commercial sectors. The forecast considers all-electric new construction and existing buildings (retrofits) that switch from a gas appliance to an electric appliance. The end-uses considered are space heating, water heating, cooking, and dryers in residential spaces. The effects of energy efficiency are not included in the BE forecast, as it is separately forecasted in PG&E's Energy Efficiency model.

b. Forecast Method Overview

The BE forecast is developed in two separate models: New Construction and Retrofits. PG&E experts provide their assessment of electrification rates given the current policy and technology outlook. These assessments are translated into end-use appliance electrification rates, which are converted into energy impact (GWh, MM Therms).

c. Forecast Method Details

i. New Construction

For the New Construction model, PG&E collaborates with its Codes & Standards team to incorporate present and potential future Title 24 Building Codes[13] and Title 20 Appliance Standards.[14] Estimates for new construction are based on data from the CEC[15]; Moody's Analytics[16]; and Landis, John, and Hood[17].

ii. Retrofit

The Retrofit model aims to estimate customer adoption of electric appliances, incorporating policy, economics, and technology, and assuming replacement at the end of the appliance's lifetime. The existing buildings in PG&E territory is informed by data from internal teams. The retrofit market potential, which includes device lifetime and efficiency, is estimated based on data and reports from the CEC[18], and EIA[19].

iii. Peak

PG&E uses the output of the New Construction and Retrofit models to determine how each end-use contributes to an aggregated BE load shape. The Peak Model determines the electric demand in each hour of every year of the forecast, as there is variation in energy consumption across different end-uses. The various end-use load shapes come from the CEC's 2019 California Investor-Owned Utility Electricity Load Shapes[20], which includes different building types in different climate zones.

d. Key Inputs and Assumptions

- **High-rise residential** buildings will behave physically like a commercial space, as they are categorized as a Non-Residential building in code standards
- For retrofits, the **addressable market** is the number of residential gas customers that currently exist that need to replace gas equipment, determined by the

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[13] California Energy Commission, 2020. Building Energy Efficiency Standards – Title 24. https://www.energy.ca.gov/programs-and-topics/programs/building-energy-efficiency-standards

[14] California Energy Commission, 2020. Appliance Efficiency Regulations – Title 20. https://www.energy.ca.gov/rules-and-regulations/appliance-efficiency-regulations-title-20

[15] California Energy Commission, 2021. California Energy Demand Mid Case value.
California Energy Commission, 2019. Residential Appliance Saturation Survey.

[16] Moody's Analytics, 2020. Building Permits.

[17] Landis, John & Hood, Heather & Li, Guangyu & Rogers, Thomas & Warren, Charles. (2006). The Future of Infill Housing in California: Opportunities, Potential, and Feasibility. Departmental Papers (City and Regional Planning). 17. 10.1080/10511482.2006.9521587.

[18] California Energy Commission, 2019. Residential Appliance Saturation Survey.
California Energy Commission, 2019. IEPR Fuel Substitution.

[19] U.S. Energy Information Administration, 2023. Updated Buildings Sector Appliance and Equipment Costs and Efficiencies. https://www.eia.gov/

[20] California Energy Commission, 2019. California Investor-Owned Utility Electricity Load Shapes. https://www.energy.ca.gov/sites/default/files/2021-06/CEC-500-2019-046.pdf

lifetime of the equipment. PG&E assumes that a customer will not replace a gas equipment until the end of the device lifetime

4. Electric Vehicle Forecast Methodology

a. Scope

PG&E forecasts plug-in electric vehicles (PEVs) and fuel cell electric vehicles (FCEVs), collectively referred to below as electric vehicles (EVs). The forecast does not address other low emission vehicle technologies such as natural gas fueled vehicles, and it is limited to on-road vehicles Classes 1-8.[21] The EV forecast consists of three components:

1) "EV population forecast": forecasts number of EVs on the road
2) "EV energy forecast": forecasts EV electric energy consumption (GWh)
3) "EV hourly load forecast": forecasts hourly average EV electric load (MW)

The EV forecast time horizon extends through 2045. The forecast includes and differentiates between light-duty vehicles (LDV), which we define here as Classes 1-2a, as well as medium- and heavy-duty vehicles (MDHDV), which we define here as Classes 2b-8. The LDV forecast considers both conventionally operated vehicles and rideshare vehicles, as well as light duty vehicles participating in Vehicle-to-Everything (V2X).

b. Forecast Method Overview

PG&E forecasts EV population using a top-down policy-based scenario model. The EV energy forecast is developed by multiplying the population forecast by daily charging rates based on the vehicle class (e.g., 1-2a, 2b-3, 4-8) and use type (e.g., rideshare, long-haul tractor). The EV hourly load forecast is produced by applying current hourly charging profiles to the energy forecast and evolving those profiles over time towards more optimized future charging shapes.

c. Forecast Method Details

i. Light-Duty (LD) EV Population and Energy

PG&E's LD EV forecast follows a scenario-based approach. Scenarios are developed considering 1) an analysis of historical (2010 through June 2024) California EV registration data and 2) internal subject matter expert opinions of EV sales market share in California. These subject matter expert opinions are primarily based on economic variables, California zero emission vehicle regulations (namely Advanced Clean Cars I and II), and state and federal EV incentives. These LD EV sales market share scenarios are then converted to population scenarios using survival functions and total vehicle sales forecast data from CARB's Scoping Plan. The average of the various

[21] U.S. Department of Energy, Alternative Fuels Data Center, https://afdc.energy.gov/data/10380 (accessed May 19, 2021)

subject matter expert population scenarios is then calculated and scaled down to match PG&E's estimated portion of statewide LDV ownership (~37%).[22]

Once this LD EV population forecast has been developed, it is translated into the LD EV energy forecast using different energy assumptions for commercial, rideshare, and personal vehicles – both those participating in vehicle-to-everything (V2X) and not. This forecast assumes personal LD EVs not participating in V2X consume an average of 8.3 kWh per vehicle per day. The other LD EV segments are assumed to have different average daily electricity consumption than personal LD EVs not participating in V2X: rideshare vehicles (4x a personal non-V2X LD EV[23]), commercial vehicles (2.14x[24]), and personal vehicles participating in V2X (varies over time[25]).

ii. Medium- and Heavy-Duty (MDHD) Population and Energy

While PG&E's MDHD EV forecast includes all on-road class 2b-8 vehicles, it distinguishes between EV transit buses and all other 2b-8 vehicles referred to here as E-Trucks, forecasting these two segments separately.

EV Transit Buses

A deterministic forecast approach is used for the transit bus segment, which reflects meeting the Innovative Clean Transit Regulation goals of 100% EV transit bus sales by 2029 and 100% EV transit bus population by 2040.[26] The EV transit bus population forecast is scaled down to match PG&E's estimated portion of statewide MDHDV ownership (~31%)[27] and then further segmented, assuming PEVs make up 85% and FCEVs make up 15% of EV transit bus population.[28]

Once the EV transit bus population is derived, the energy impact is calculated using energy consumption per vehicle per year data provided in the CalETC - TEA Study Phase 3[29] and internal SME assumptions for FCEV energy consumption. These assumptions include how much hydrogen production via electrolysis increases demand for electricity on PG&E's distribution system.

E-Trucks

To forecast annual energy, the E-Truck population forecast is multiplied by the appropriate energy consumed per vehicle per day assumption for each subsector of E-Truck (Class 2b-3, Class 4-7 non-tractor, Class 8 non-tractor, Class 7 tractor, and Class 8 tractor) and fuel type (PEV or FCEV). The energy per vehicle per day assumption

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[22] Based on internal analysis of CEC 2021 IEPR EV population forecast data for PG&E's planning area and the entire state.

[23] Internal analysis based on discussions with charging providers and the following paper: Alan Jenn, Emissions Benefits of Electric Vehicles in Uber and Lyft Services, 2019

[24] Based on internal analysis of average fuel economy and VMT of class 1-3 model EVs

[25] Based on internal vehicle-to-everything modeling

[26] ICT Factsheet: https://ww2.arb.ca.gov/resources/fact-sheets/innovative-clean-transit-ict-regulation-fact-sheet#:~:text=The%20ICT%20regulation%20was%20adopted,for%20full%20transition%20by%202040.

[27] Based on internal analysis of CEC 2021 IEPR EV population forecast data for PG&E's planning area and the entire state.

[28] Informed by internal subject matter expert assumptions and analysis of ICT Rollout Plans available as of November 2020.

[29] Page 18: CalETC – TEA Study Phase 3

data for each E-Truck subsector is calculated from a more detailed analysis of vehicle miles traveled (VMT)[30] and energy consumed per mile traveled data.[31]

The sum of the EV transit bus and E-Truck energy forecasts constitutes the MDHD EV energy forecast. The sum of the MDHD EV and LD EV energy forecasts constitutes the total EV energy forecast.

iii. Hourly Average EV Load (MW)

PG&E's hourly average EV load forecast builds off the EV energy forecast by applying hourly charging profiles to the daily energy consumption values. Normalized load shapes include: 1) LDV home-charging on a TOU rate[32], 2) LDV home-charging on a non-TOU rate[33], 3) LDV public charging via DC fast chargers[34], 4) LDV public charging via non-DC fast chargers[35], 5) LD commercial vehicle charging[36], 6) E-Truck charging[37], 7) EV transit bus charging[38], and 8) hydrogen electrolysis (for FCEV transit buses and E-Trucks). Additionally, for LDVs participating in V2X, a (non-normalized) load profile – developed from internal V2X modeling – is used as V2X load impacts include charging and discharging.

PG&E defines current hourly load shapes based on studies and measured data, where possible. The source of assumed future hourly load shapes varies for vehicle charging class. For LD home-charging and MDHD EV charging, load shapes for the late 2030s/early 2040s were deduced via internal SME input (considering factors such as temporal distribution of wholesale energy prices, time-of-use rate evolution, availability of "smart charging" technology, and commute patterns), as well as external research. For LDV charging away from home, load shapes for 2035 and 2042 were created based on external studies.[39] V2X load profiles are designed to resemble front-of-meter storage dispatch patterns, based on system-level optimization analyses.

d. Key Inputs, Assumptions, and Observations

Key inputs, assumptions, and observations not described in the preceding sections are listed below.

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[30] Informed by Forest, Kate E., 2019, Zero-Emission Heavy-Duty Vehicle Integration in Support of a 100% Renewable Electric Grid.

[31] Informed by "Estimating the technical feasibility of fuel cell and battery electric vehicles for the medium and heavy duty sectors in California" by Forrest et al., https://www.sciencedirect.com/science/article/abs/pii/S030626192030951X

[32] 2016 Convergence Data Analytics (CDA) study of EV-B Rate customers for PG&E

[33] PG&E internal analysis – Clean Transportation Team

[34] PG&E internal database- Aggregated data from DC fast charging stations in PG&E's service territory

[35] SCE's Charge Ready Pilot/ Q3 Report: https://www.sce.com/sites/default/files/inline-files/CR%20QuarterlyReport_2018%20Q3%20r1%20%281%29.pdf

[36] Assumed to be the same as for E-Truck charging

[37] PG&E internal data – PG&E worked with its automation industry partners to create PG&E's rates and programs for the electric commercial fleet. Load profiles provided by industry partners were used as bases for the E-Truck and E-Bus load shapes.

[38] ibid

[39] Powell et al. "Charging infrastructure access and operation to reduce the grid impacts of deep electric vehicle adoption" and CEC's "Assembly Bill (AB) 2127 Electric Vehicle Charging Infrastructure Assessment"

- All LD EVs are assumed to be PEVs, with no distinction made between plug-in hybrids and full battery electric vehicles.
- Electric and combustion vehicles have equivalent life cycles.
- Smart charging infrastructure is flexible and reacts to price signals.
- Average vehicle energy consumption (kWh/vehicle/day), of a specific vehicle type, does not change over the forecast horizon.
- Average morning and afternoon commute patterns do not change throughout the forecast time horizon.
- Time-varying rates for EV charging generally reflect wholesale pricing signals.
- Use of EVs for rideshare grows according to Transportation Network Company's commitments to transition to ZEVs and CARB's Clean Miles Standard regulation.
- V2X customers will reserve a significant portion of their EV battery for mobility and security.
- The ratio of EVs which adhere to the various charging profiles exhibit some changes throughout the forecast time horizon.
    - While at-home charging remains the dominant method of LD personal EV charging throughout the forecast horizon, the prevalence of public charging grows at the expense of at-home charging.[40]
    - Non-rideshare vehicles remain the dominant type of LD EV throughout the forecast horizon, but the rideshare to non-rideshare proportion mostly grows throughout forecast.[41]
    - While the prevalence of public DCFC and public L2 charging remains about equal for non-rideshare LD personal EVs, the rideshare sector's growth results in a much greater share of charging from public DCFC (than public L2) for non-commercial LD EVs (personal + rideshare).

5. Energy Efficiency Forecast Methodology

a. Scope

PG&E forecasts the impact of energy efficiency (EE) savings on PG&E's system over a forecast horizon of 2025-2045. The forecast leverages the California Energy Commission (CEC) Integrated Energy Policy Report (IEPR)/California Energy Demand (CED) forecast data. PG&E forecasts two separate savings streams as described below:

- Committed EE savings, in GWh, derived from the CED 2019 committed electricity savings mid-demand case annual data, provided by the CEC directly to PG&E, and adjusted to reflect more recent trends in savings

[40] Based on data from the CEC's "Assembly Bill (AB) 2127 Electric Vehicle Charging Infrastructure Assessment"

[41] Based on BNEF's forecast of US EV "shared" fleet

- Uncommitted EE savings, in GWh, derived from 2023 IEPR scenario-specific additional achievable energy efficiency (AAEE) annual data, provided by the CEC directly to PG&E

b. Forecast Method Overview

PG&E requires a twenty-year forecast of its electric system for resource planning purposes, so the source data is extrapolated and adjusted to represent only savings on PG&E's electric distribution system. After these processing steps, the committed EE savings data from the 2019 CED forecast – adjusted to reflect more recent trends in savings – becomes PG&E's committed EE savings forecast. The scenario-specific uncommitted EE savings data from the 2023 IEPR AAEE forecast are presented to internal subject matter experts (SMEs) for weighting. The resulting weighted average uncommitted EE savings forecast is added to the committed EE savings forecast to produce the total annual EE savings forecast. This annual forecast is then transformed into an hourly forecast using PG&E-specific and end-use-specific load shapes from the CEC's 2019 IOU Electricity Load Shape study.

c. Forecast Method Details

i. Source Data

The energy efficiency forecast employs the CEC's 2023 IEPR AAEE and 2019 CED committed electricity savings forecast data, both of which are informed by the California Public Utilities Commission (CPUC)'s Potential and Goals (P&G) study that is developed and used by policymakers to establish IOU goals. The IEPR AAEE forecast data is also informed by the CEC's "Beyond Utility" tool and the CMUA PG study for POU projections. PG&E would have used updated CED data on committed electricity savings, but this data is no longer being produced for the IEPR forecast. Consequently, in an effort to reflect more recent trends in savings in our service territory, the 2019 CED committed savings data was adjusted using trends from the CEDARS database[42].

This hybrid source data must be processed in order to be compatible with PG&E's forecasting methodology. First, as PG&E's forecast covers a twenty-year period, each of the forecasts must be extrapolated from their final year (2040 for the 2023 IEPR, 2030 for the 2019 CED) to 2045, the end of the forecast horizon. Additionally, the 2024 source data must be subtracted from each of the years thereafter such that all data is cumulative to 2024. Finally, the source data must be modified to only represent savings on PG&E's electric distribution system.

ii. Committed EE Annual Savings Forecast

PG&E uses the 2019 CED mid-demand case data (and the CEDARS data trends) to develop its committed EE savings forecast. Committed savings are defined as expected energy savings from "on-the-books" building codes and appliance standards (C&S) as well as programs with funding commitments or implementation plans. This savings stream is considered relatively certain to occur, and the savings are based on the expected useful life (EUL) of each measure or C&S technology installed. The mid

[42] https://cedars.cpuc.ca.gov/monthly-reports/confirmed-dashboard/PGE/

energy demand scenario (influenced by economics, technology, etc.) has traditionally been used for various regulatory proceedings. Aside from the extrapolation and conversion from PG&E TAC area (what the CEC's calls "planning area") to PG&E service area, the 2019 CED forecast data is used directly as PG&E's committed EE savings forecast.

iii. Uncommitted EE Annual Savings Forecast

PG&E uses the 2023 IEPR scenario-specific AAEE data to create an uncommitted EE savings forecast. Uncommitted savings are defined as incremental energy savings from future market potential that is reasonably expected to occur through future updates of building codes, appliance standards, and new or expanded programs, though these updates and programs have yet to be implemented or funded. Internal SMEs consider the various AAEE scenarios and assign probabilistic weights to them, specific to near-term (2025-2027), mid-term (2028-2031), and long-term (2032-2045) timeframes (as market drivers can be substantially different over time). The resulting weighted average uncommitted EE savings forecast is added to the committed EE savings forecast to produce the total annual EE savings forecast.

iv. Net to Gross

Finally, the total annual EE savings forecast is converted from net savings to gross savings. This step is performed as both committed EE and AAEE savings data are typically provided as net, rather than gross, savings. Gross EE includes all the savings the grid will see, while net EE excludes free riders.[43] Net savings are effectively only what the IOUs can claim as savings. The net savings are "grossed up" using recent historical net-to-gross ratios and the 2023 IEPR AAEE mid forecast breakdown between programs and C&S.

v. Hourly Forecast

The hourly forecast uses the total annual EE savings forecast to construct the demand (MW) over each hour of the twenty-year forecast. Technically, a simplified "daytype" forecast for energy efficiency hourly impacts, rather than a comprehensive 8760 forecast, is produced using weekday, weekend, and peak daytypes for each month and year.

The California Energy Commission's 2019 IOU Electricity Load Shape study provides PG&E-specific load shapes for a variety of end-uses, used to shape annual EE savings for each hour and estimate peak impacts. The model looks at committed and uncommitted shaping separately, categorizing the different end-uses for various measures.

d. Key Inputs, Assumptions, and Observations

Key inputs, assumptions, and observations not described in the preceding sections are listed below.

[43] Free riders are those who accept rebates or incentives even though they would've completed the EE upgrade without the financial incentive. In measuring the program performance metrics, free ridership is removed from the total savings claims.

- Future electric EE savings seem to driven by C&S more than programs and by the committed sectors. That is, savings from new C&S and programs are limited relative to “on-the-books” savings.

Coincident Peak Calculation Methodology

For each load modifier discussed in the Load Modifier Forecast Methodologies section above (battery storage, BTM solar PV, building electrification, electric vehicle, and energy efficiency), a similar process is followed for calculating the “Peak Demand Impact - Coincident with LSE Annual Peak,” referred to here as “coincident peak.”

First, the forecasted annual system peak hour and month for each year from 2025-2036 are identified. Next, the annual coincident peak for a modifier is calculated as the average load modification from that modifier in that year’s annual system peak hour and month. This is done for each year from 2025-2036. To calculate a modifier’s 2024 baseline coincident system peak, the recorded 2024 system peak hour and month are identified. The 2024 historical system peak is then used as the baseline coincident peak value and subtracted from the coincident peak values for each year from 2025-2036.

Post COVID Usage Patterns

PG&E notes that post-COVID changes in residential and commercial electric usage behavior, in particular working from home, have persisted to some degree. To estimate this effect, PG&E calculated (historical) post-COVID annual impacts using dummy variables and extrapolated this effect into the future using a simple exponential curve. For this year, this results in a long term effect on the order of a couple of percent, larger for commercial than for residential.

Incorporating Energy Efficiency and Distributed Generation in the Forecast

PG&E incorporates energy efficiency and distributed generation impacts in demand forecasting by performing a series of steps:

1. EE/DG savings data is gathered to find the average impacts during the regression period.

2. The average EE/DG impact is compared to future EE/DG savings projections in the forecast period.

3. If the future EE/DG impact is projected to be greater than past EE/DG impact, the forecast is decremented by the difference.

Incorporating Electric Vehicles in the Forecast

Since electric vehicles are a relatively new factor in the sales forecast, PG&E simply adds all expected EV sales and peak impact to the overall sales forecast.

Incorporating Building Electrification in the Forecast

PG&E takes a similar approach for building electrification compared to EV, and simply adds expected building electrification sales and peak impact to the overall forecast.

Calculating Bundled Sales

Once the system level forecast is completed, PG&E updates its forecast for direct access and community choice aggregation departures to derive the bundled sales forecast. The following section details this forecasting methodology and key assumptions.

Estimates of Direct Access, Community Choice Aggregation, and Other Departed Load

a. Scope

The forecast scope includes the sales and customers of Community Choice Aggregation (CCA) and Direct Access (DA) load-serving entities (LSEs) in PG&E's service territory. The forecast allocates PG&E system sales and customers to each CCA and aggregate DA Energy Service Providers (ESPs), segmented by rate sector (Agriculture, Large Commercial/Industrial, Medium Commercial, Residential, Small Commercial, Streetlights). The forecast does not allocate DA by individual ESP.

b. Forecast Method Overview

CCA and DA sales and customers are forecasted using system growth in each sector, as well as any expansions or new formations of LSEs. Where known, CCA and DA expansions are added to the forecast. Additionally, assumptions about probable new CCA expansions and formations impact the sales and accounts forecast.

c. Forecast Method Details

- The forecast relies on customer billing data for the most recent year of recorded data (2024) to quantify current sales and customers served by CCA and DA LSEs. Data are aggregated by LSE, city, month, and sector and provide a complete year of metered usage and accounts.
- For CCAs, sales and customer growth are forecasted by applying monthly, sector-level growth rates derived from the system sales and accounts forecast.
- Known CCA expansions and new formations are forecasted by adding communities' sales and accounts to existing or new CCA LSEs.

- A portion of CCA sales and customers come from probable CCAs where an implementation plan does not exist, but PG&E expects the community to enter CCA service sometime during the forecast time horizon.
- Growth in DA reduces CCA sales and customers. Where known (for the expansion to the current cap), DA sales and customers are allocated from each CCA based on current LSE and location.
- Bundled sales and accounts can be calculated by subtracting CCA, DA, and BART sales and accounts from the total system for each sector and period.

d. Key Inputs and Assumptions

- Forecasted sales and accounts departing from PG&E Bundled service to CCA service do not return to PG&E service under the current model framework; similarly, sales and accounts allocated from CCA service to DA service do not return to CCA service.
- Sector-level growth rates relative to the current year are produced for the total PG&E system for each period of the system forecast and do not vary geographically.
- PG&E models CCA opt-outs by excluding some portion of new forecasted sales and accounts from each CCA. That opt-out portion is calculated from recorded data and varies by CCA and sector. Where unknown, average sector opt-out rates are applied to new communities joining or forming a CCA in the forecast.
- CCA names, service territories, phase-in schedules, implementation plans, and other activities determine which communities enter CCA service, when a community enters CCA service, and how much of that community's sales and accounts should be forecasted for that CCA. Once filed, PG&E assumes a CCA or expansion will follow the schedule described in its implementation plan.
- To forecast formation/expansion of a new CCA without an implementation plan, PG&E assumes a probability of departure to calculate an expected value for each forecast period.
- The DA forecast relies on known information about customers departing from PG&E Bundled or CCA service. DA expansion customers and usage data are required to forecast new DA growth and allocate sales and accounts from individual CCAs in the forecast.
- Post-COVID estimated changes in load due to work practices are based on recorded billing data during the pandemic and modify forecasted CCA and DA sales by sector. The effects of COVID decrease over time but are estimated to have a small persistent effect.
- PG&E assumes no additional DA reopening (beyond the current cap of 11,400 GWh per year) in the 2025-2036 timeframe.

Weather Adjustments

Weather adjustment of historical sales and peak data is accomplished by the inclusion of temperature variables within the regression equations. Daily temperatures are converted to degree days. Cooling degree days use 75° F as a base, while heating degree days are calculated with a base of 60° F. The residential sector includes both HDDs and CDDs in its regression equation, while the commercial equation includes only CDDs. PG&E has not found a statistically significant relationship between commercial usage and heating degree days, suggesting that commercial HVAC systems consume no more energy to heat a building than they do to provide basic ventilation. PG&E has also found that the industrial sector is temperature sensitive to CDDs, and as such, includes CDD in the large commercial and industrial regression equation.

PG&E uses CDDs and HDDs calculated on a system-wide basis. Eleven reporting stations are employed, weighted by sales. The weights are shown in the table below:

	Heating Weights	Cooling Weights
Redding	4%	4%
Fresno	15%	21%
Sacramento	19%	20%
Santa Rosa	7%	7%
Eureka	2%	1%
Oakland	14%	12%
San Jose	18%	16%
San Rafael	2%	2%
Salinas	6%	5%
Livermore	11%	11%
Paso Robles	2%	1%

Calculating Losses

Historical losses can be estimated by calculating the difference between metered sales and retail generation. For the forecast period, PG&E uses a formulaic approach. Distribution losses are calculated as a non-linear function of the level of system load according to study results; transmission losses and unaccounted for energy (UFE) are calculated as 3 percent of load per Resource Adequacy instructions.

Calculating Hourly Loads

PG&E forecasts the 1 in 2 (expected) hourly loads by using a typical monthly set of hourly load values generated from historical data and, after adjusting for hourly forecasts of Load Modifiers such as EVs and distributed generation, scales the result to match forecast total energy and peak. The typical load value distribution is forecast in such a way to map historical daily price shapes for a given day type to future occurrences of that day type.

Reasonableness of Forecast and Accuracy

PG&E believes these forecasts which show a stability in system sales, somewhat declining bundled sales, and slightly increasing peaks in the short term are reasonable given recent load loss due to the rapid growth of distributed generation and expected impacts of energy efficiency. Electric vehicles, new data centers, and building electrification are important, but only in the latter years of the forecast do they start to push sales up. PG&E is already losing considerable bundled load to CCAs, and PG&E expects this trend to continue more slowly as other municipalities actively pursue CCA programs.

PG&E's peak shift analysis shows a system coincident peak shift out to later hours than assumed in historical regression modeling. By 2026, the system coincident peak hour is forecast to be 7 PM, due to the expansion of BTM PV. Later dated peak hours may be even later, but depends on the details of EV and storage operation. EV charging and building electrification peak impacts are offset by BTM storage discharging during peak hours and incremental energy efficiency impacts.

PG&E's system forecasting approach is typically accurate to within 1 percent in the short-term (1 – 2 years) and less accurate in the long-term.