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Notes of Pacific Gas and Electric Company
2021 IEPR Demand Forms for the California Energy Commission
July 30, 2021
Docket 21-IEPR-03
FORM 4

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

Form 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 2020. 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 1.1b.

In the forecast period 2021-2040, PG&E has included the effects of energy efficiency as described in the Section III, Demand Forecast Methods, below. PG&E has also included the impacts of electric vehicles, 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 confidentiality applications submitted with these forms.

Form 1.2 Distribution Area Net Electricity for Generation Load

DA and CCA load are provided in Form 1.2. DA load is expected to increase in 2021 as the cap rises due to SB 237. 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. Therefore, uncommitted impacts of energy efficiency (Column L) are shown as negative values in order not to double count EE. Column M shows the load gross of uncommitted EE.

PG&E is requesting confidential treatment for various portions of Form 1.2 as discussed in the confidentiality applications 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's 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, electric vehicles, and electrification are included in the forecast data. In addition, the impacts of customer-owned storage and 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.

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 confidentiality applications submitted with these forms.

Form 1.6a Distribution Area Hourly Load

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 2019 and 2020 are consistent with the distribution loss factor algorithms used in the Settlements process. Forecasted distribution losses for 2022 are based upon historical estimates of these losses.

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 confidentiality applications submitted with these forms.

Form 1.6b Hourly Loads by Transmission Planning Subareas or Climate Zone (IOUs Only)

The breakdown shows the recorded hourly load for various local areas for 2019 and 2020 and includes bundled and unbundled load.

PG&E does not forecast load by local areas and hence hourly load by local areas is not available for 2022.

II. Forecast Input Assumptions

Form 2.1 PG&E Planning Area Economic and Demographic Inputs

Inputs are drawn from Moody's Analytics December 2020 baseline projections for PG&E's service area economy.

Form 2.2 Electricity Rate Forecast

PG&E reviewed and updated the 2021 regression models for the class accounts and load forecasts. The residential rate variable used in the residential regression for the 2019 and 2020 load forecasts was in both years statistically insignificant and therefore did not contribute to explaining the usage of residential customers. The commercial rate variable used in the commercial regression for the 2019 and 2020 forecasts was in both years marginally significant. Its contribution to explaining the usage of commercial customers was best left to more significant drivers and removed from the model. The industrial and agricultural regression models for 2019 and 2020 did not include rate variables. The 2021 load forecast models did not contain rate variables and therefore Form 2.2 in the 2021 IEPR filing is blank. Forward looking revenue requirements will be included in Forms 8.1a and 8.1b.

Form 2.3 Customer Count & Other Forecasting Inputs

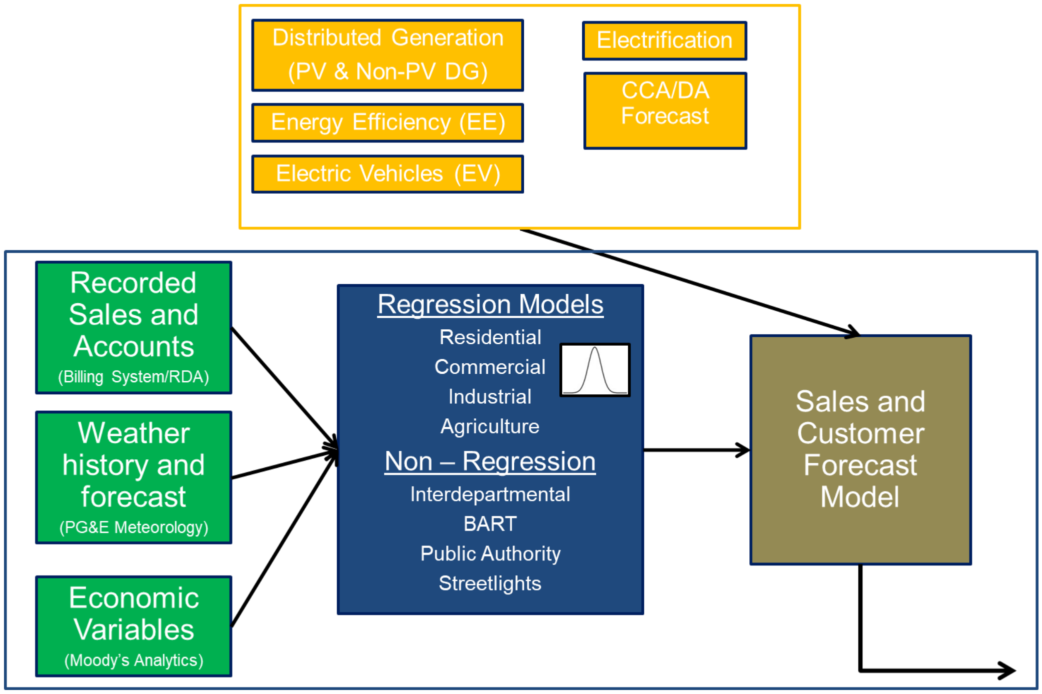
Form 2.3 provides recorded and projected customer counts by customer class. The data reported is billing data (number of bills), which is used to represent number of customers. The annual numbers reported are averages of 12 months of customer data.

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, electric vehicles, building electrification, 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, Electric Vehicles (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 auto-correlation 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.

PG&E models COVID impacts by class using a dummy variable that covers the historical months of COVID up to the end of 2020 and extends to June of 2023. The impact of this variable is ramped down linearly starting in May of 2021, ending at zero in June of 2023. There is no impact after June of 2023, although economic outlooks may implicitly contain longer term effects. This is a simplified model intended to capture the effect of COVID on sales.

Model Components

Equations for the four major customer class energy forecasts are shown below (pp. 7-12):

Residential Accounts

Dependent Variable: D(RES_ACCTS_IDA)				
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)				
Date: 02/16/21 Time: 08:31				
Sample: 2003M06 2020M12				
Included observations: 211				
Convergence achieved after 5 iterations				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
PPH	-573.6065	304.6295	-1.8830	0.0612
SINGLE_FAMILY_PERMITS	0.0648	0.0121	5.3734	0
MULTI_FAMILY_PERMITS	0.0172	0.0385	0.4471	0.6553
JAN	2116.2100	887.7560	2.3838	0.0181
FEB	522.3890	896.3374	0.5828	0.5607
MAR	4338.6670	903.7274	4.8009	0
APR	2517.8830	905.7010	2.7800	0.006
MAY	5318.3450	903.0542	5.8893	0
JUN	8429.3620	887.2125	9.5010	0
JUL	4917.3300	885.8569	5.5509	0
AUG	8305.9870	884.5372	9.3902	0
SEP	-2416.3290	878.0939	-2.7518	0.0065
OCT	-4976.3670	832.2043	-5.9797	0
DEC	-2177.5440	831.1665	-2.6199	0.0095
AR(1)	0.1064	0.0716	1.4865	0.1388
R-squared	0.740628	Mean dependent var		2898.512
Adjusted R-squared	0.722102	S.D. dependent var		4975.658
S.E. of regression	2622.971	Akaike info criterion		18.65044
Sum squared resid	1.35E+09	Schwarz criterion		18.88872
Log likelihood	-1952.621	Hannan-Quinn criter.		18.74676
Durbin-Watson stat	1.97E+00			

PPH = People Per Household which is computed as PPH=POP_PGE/HH_PGE (where POP_PGE refers for population and HH_PGE is number of households in PG&E Territory)

SINGLE_FAM_PERMS_PGE = Single family house permits

MULTI_FAM_PERMS_PGE = Multi-family house permits

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

Residential Usage per Account

Dependent Variable: LOG(RES_SALES_IDA/RES_ACCTS_FORE)				
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)				
Date: 02/16/21 Time: 08:53				
Sample (adjusted): 2004M02 2020M12				
Included observations: 203 after adjustments				
Convergence achieved after 11 iterations				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.9004	0.1766	33.4194	0
HDD	0.0005	0.0001	10.0195	0
CDD	0.0022	0.0001	17.0174	0
COVID_MAR_2020_JUN2023	0.0768	0.0174	4.4239	0
AR(1)	0.4977	0.0632	7.8777	0
SAR(12)	0.9482	0.0350	27.1285	0
R-squared	0.9558	Mean dependent var		6.2795
Adjusted R-squared	0.9547	S.D. dependent var		0.1353
S.E. of regression	0.0288	Akaike info criterion		-4.2278
Sum squared resid	0.1634	Schwarz criterion		-4.1299
Log likelihood	435.1218	Hannan-Quinn criter.		-4.1882
F-statistic	852.3810	Durbin-Watson stat		1.9408
Prob(F-statistic)	0.0000			

COVID_MAR_2020_JUN2023 = dummy variable for covid pandemic from March 2020 to June 2023

HDD = Heating Degree Days (PG&E Territory)

CDD = Cooling Degree Days (PG&E Territory)

Commercial Accounts

Dependent Variable: D(COM_ACCTS_IDA)				
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)				
Date: 02/16/21 Time: 09:06				
Sample: 2003M01 2020M12				
Included observations: 216				
Convergence achieved after 6 iterations				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	93.22131	37.48905	2.486628	0.0137
D(RES_ACCTS_FORE)	0.0360	0.0064	5.6382	0
Apr-13	-3296.2400	455.1876	-7.2415	0
Jan-03	-3089.6860	483.8869	-6.3851	0
Jan-04	4425.7840	457.1858	9.6805	0
May-13	3180.1240	454.8574	6.9915	0
Oct-17	463.3678	457.6656	1.0125	0.3125
AR(1)	0.0304	0.071383	0.426538	0.6702
R-squared	0.5903	Mean dependent var		203.2176
Adjusted R-squared	0.5765	S.D. dependent var		697.2996
S.E. of regression	453.7845	Akaike info criterion		15.10946
Sum squared resid	42831436	Schwarz criterion		15.23447
Log likelihood	-1623.8210	Hannan-Quinn criter.		15.1600
F-statistic	42.8094	Durbin-Watson stat		1.9673
Prob(F-statistic)	0.0000			

C = Constant
RES_ACCTS_IDA_F = residential accounts forecast
APR2013 = Month dummy to clean regression results for outlier data point.
Jan2003 = Month dummy to clean regression results for outlier data point.
Jan2004 = Month dummy to clean regression results for outlier data point.
May2013 = Month dummy to clean regression results for outlier data point.
Sept2017 = Month dummy to clean regression results for outlier data point.

Commercial Usage per Account

Dependent Variable: LOG(COM_SALES_IDA/COM_ACCTS_F)				
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)				
Date: 02/16/21 Time: 10:16				
Sample (adjusted): 2004M02 2020M12				
Included observations: 203 after adjustments				
Convergence achieved after 17 iterations				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.6706	0.1766	43.4250	0.0000
LOG((EMP_FIN_ACT_PGE+EMP_INFO_PGE+EMP_TOT_SVC_PGE)/EMP_TOT_PGE)	-1.2123	0.2691	-4.5047	0.0000
COVID_MAR_2020_JUN2023	-0.1389	0.0139	-9.9796	0.0000
CDD	0.0009	0.0001	10.6473	0.0000
AR(1)	0.5940	0.0594	10.0054	0.0000
SAR(12)	0.6862	0.0588	11.6715	0.0000
R-squared	0.9517	Mean dependent var		8.5144
Adjusted R-squared	0.9504	S.D. dependent var		0.0917
S.E. of regression	0.0204	Akaike info criterion		-4.9162
Sum squared resid	0.0821	Schwarz criterion		-4.8183
Log likelihood	504.9968	Hannan-Quinn criter.		-4.8766
F-statistic	775.5579	Durbin-Watson stat		2.1553
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)

CDD = Cooling Degree Days (PG&E Territory)

COVID_MAR_2020_JUN2023 = dummy variable for covid pandemic from March 2020 to June 2023

Industrial Sales

Dependent Variable: LOG(IND_SALES_IDA_2_5/IND_ACCTS_IDA_2_5_FORECAST)				
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)				
Date: 02/16/21 Time: 09:43				
Sample (adjusted): 2003M02 2020M12				
Included observations: 215 after adjustments				
Convergence achieved after 7 iterations				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.172E+01	0.5420	21.6205	0
LOG(GDP_MANUFACTURING)	1.732E-01	0.0463	3.7389	0.0002
CDD	4.370E-04	0.0001	3.2630	0.0013
JAN	1.016E-02	0.0068	1.4940	0.1368
FEB	1.668E-02	0.0088	1.8939	0.0597
MAR	6.049E-02	0.0100	6.0494	0
APR	6.178E-02	0.0108	5.7117	0
MAY	6.522E-02	0.0122	5.3581	0
JUN	6.115E-02	0.0161	3.7897	0.0002
JUL	8.638E-02	0.0211	4.0994	0.0001
AUG	1.105E-01	0.0202	5.4752	0
SEP	1.184E-01	0.0153	7.7534	0
OCT	8.343E-02	0.0096	8.6699	0
NOV	5.528E-02	0.0066	8.3299	0
COVID_MAR_2020_JUN2023	-4.501E-02	0.0224	-2.0077	0.046
AR(1)	7.593E-01	0.0465	16.3257	0
R-squared	0.8725	Mean dependent var		1.38E+01
Adjusted R-squared	0.8629	S.D. dependent var		0.0716
S.E. of regression	2.652E-02	Akaike info criterion		-4.3501
Sum squared resid	1.400E-01	Schwarz criterion		-4.0993
Log likelihood	483.6382	Hannan-Quinn criter.		-4.2488
F-statistic	90.8202	Durbin-Watson stat		2.1948
Prob(F-statistic)	0.0000			

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

COVID_MAR_2020_JUN2023 = dummy variable for covid pandemic from March 2020 to June 2023

Agricultural Sales

Dependent Variable: LOG(AG_SALES_IDA_2_5/AG_ACCTS_FORE)				
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)				
Date: 02/16/21 Time: 09:50				
Sample: 2000M11 2020M12				
Included observations: 242				
Convergence achieved after 9 iterations				
MA Backcast: OFF				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.720E+00	1.91E+00	2.471681	0.0142
RAIN01	0.003669	0.0109	0.337396	0.7361
RAIN02	-0.010117	0.0085	-1.191825	0.2346
RAIN03	-0.012099	0.0046	-2.60325	0.0099
RAIN04	-0.017451	0.0041	-4.223554	0
RAIN05	-0.023094	0.0040	-5.800786	0
RAIN06	-0.017857	0.0035	-5.17333	0
RAIN07	-0.014556	0.0034	-4.282069	0
RAIN08	-0.013265	0.0032	-4.158984	0
RAIN09	-0.007139	0.0031	-2.274382	0.0239
RAIN10	-0.002018	0.0030	-0.677397	0.4989
RAIN11	-0.000316	0.0026	-0.119627	0.9049
RAIN12	-0.001095	0.0020	-0.535643	0.5928
PDSI	-0.027115	0.0094	-2.881665	0.0044
LOG(AG_OUTPUT)	0.309813	0.1853	1.672284	0.0959
JAN	0.116419	0.0511	2.279523	0.0236
FEB	4.556E-01	0.0687	6.6331	0
MAR	0.63884	0.077755	8.216083	0
APR	0.9395	0.086246	10.89302	0
MAY	1.2344	0.08839	13.96553	0
JUN	1.267E+00	0.088646	14.29255	0
JUL	1.214E+00	0.086538	14.02841	0
AUG	1.0693	0.080588	13.26899	0
SEP	0.8532	0.071405	11.94881	0
OCT	0.5555	0.045601	12.1822	0
NOV	0.265843	0.042376	6.273441	0
AR(1)	0.884456	0.036738	24.07436	0
MA(1)	-0.136133	0.079496	-1.712448	0.0883
R-squared	0.976464	Mean dependent var		8.441739
Adjusted R-squared	0.9735	S.D. dependent var		0.520301
S.E. of regression	0.0847	Akaike info criterion		-1.99078
Sum squared resid	1.536E+00	Schwarz criterion		-1.5871
Log likelihood	2.689E+02	Hannan-Quinn criter.		-1.82816
F-statistic	328.8320	Durbin-Watson stat		1.967259
Prob(F-statistic)	0.0000			

C = Constant

AG_OUTPUT = PG&E service area Ag GDP (Moody's Analytics) Gross Product: Agriculture; Forestry; Fishing and Hunting (Mil. $)

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

Assuming return to normal rainfall

RAIN01 – RAIN 12 are monthly rainfall variables starting from October and running cumulatively through September

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

Post-Regression Adjustments

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

**Redacted text due to confidentiality of material.*

2. Behind-the-Meter Solar Forecast Methodology

**Redacted text due to confidentiality of material.*

3. Building Electrification Forecast Methodology

**Redacted text due to confidentiality of material.*

4. Electric Vehicle Forecast Methodology

**Redacted text due to confidentiality of material.*

5. Energy Efficiency Forecast Methodology

**Redacted text due to confidentiality of material.*

6. Non-PV Distributed Generation (Non-PV DG) Forecast Methodology

**Redacted text due to confidentiality of material.*

Coincident Peak Calculation Methodology

**Redacted text due to confidentiality of material.*

Covid Post Process Ramp Down

PG&E assumes that all explicit load impacts of covid ramps down over the next two years consistent with internal expectations and scenarios supplied by Moody's Analytics.

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 Stationary Electrification in the Forecast

This is the fourth year PG&E has forecasted the load impacts of building electrification. PG&E takes a similar approach for stationary electrification compared to EV, and simply adds expected stationary 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 (2020) 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 total system for each sector and period.

b. 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.
- For the expansions to the current DA cap of 11,400 GWh per year, the DA forecast relies on known information about customers departing from PG&E Bundled or CCA service. DA expansion customers and usage data is required to forecast new DA growth and allocate sales and accounts from individual CCAs in the forecast.
- COVID impacts 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 and are removed after the first several years of the forecast.
- PG&E assumes no additional DA reopening (beyond the current cap of 11,400 GWh per year) in the 2021-2032 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 75º F as a base, while heating degree days are calculated with a base of 60º 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%	5%
Fresno	14%	20%
Sacramento	19%	21%
Santa Rosa	7%	6%
Eureka	1%	1%
Oakland	14%	11%
San Jose	19%	16%
San Rafael	3%	2%
Salinas	7%	5%
Livermore	10%	11%
Paso Robles	2%	2%

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 electric vehicles 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.

Form 1.6b contains data for various subareas, also referred to as local areas. The local areas shown on the form are defined in the publicly available CAISO's "Local Capacity Technical Report," which is published annually on the following website: https://www.caiso.com/informed/Pages/StakeholderProcesses/LocalCapacityRequirementsProcess.aspx.

The subarea load data is derived from PG&E's electric transmission SCADA (Supervisory Control & Data Acquisition) system. The data is a proxy of load data in that it measures transmission line flows and generation output within the given subarea.

Reasonableness of Forecast and Accuracy

PG&E believes these forecasts which show a short-term stability in system sales, somewhat declining bundled sales, and declining peaks are reasonable given recent load loss due to the rapid growth of distributed generation and expected impacts of energy efficiency. Electric vehicles 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 2022, the system coincident peak hour is assumed to be 8pm, predominantly due to the rapid expansion of BTM PV. 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 run (1 – 2 years) and less accurate in the long run.