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Notes of Pacific Gas and Electric Company
2019 IEPR Demand Forms for the California Energy Commission
April 15th, 2019
Docket 19-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 2018. 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 2019-2030, 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 forecasts in Form 6.

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 2020 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

DA / CCA 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 2017 and 2018 are consistent with the distribution loss factor algorithms used in the Settlements process. Forecasted distribution losses for 2019 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 2017 and 2018 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 2019.

II. Forecast Input Assumptions

Form 2.1 PG&E Planning Area Economic and Demographic Inputs

Inputs are drawn from Moody's Analytics December 2018 baseline projections for PG&E's service area economy.

Form 2.2 Electricity Rate Forecast

The 2018 average rates are derived from the 2018 Annual Electric True-Up. Beyond 2018, rates are escalated assuming full recovery of revenue requirements and escalation at CPI.

PG&E is requesting confidential treatment for various portions of Form 2.2 as discussed in the confidentiality applications submitted with these forms.

Form 2.3 Customer Count & Other Forecasting Inputs

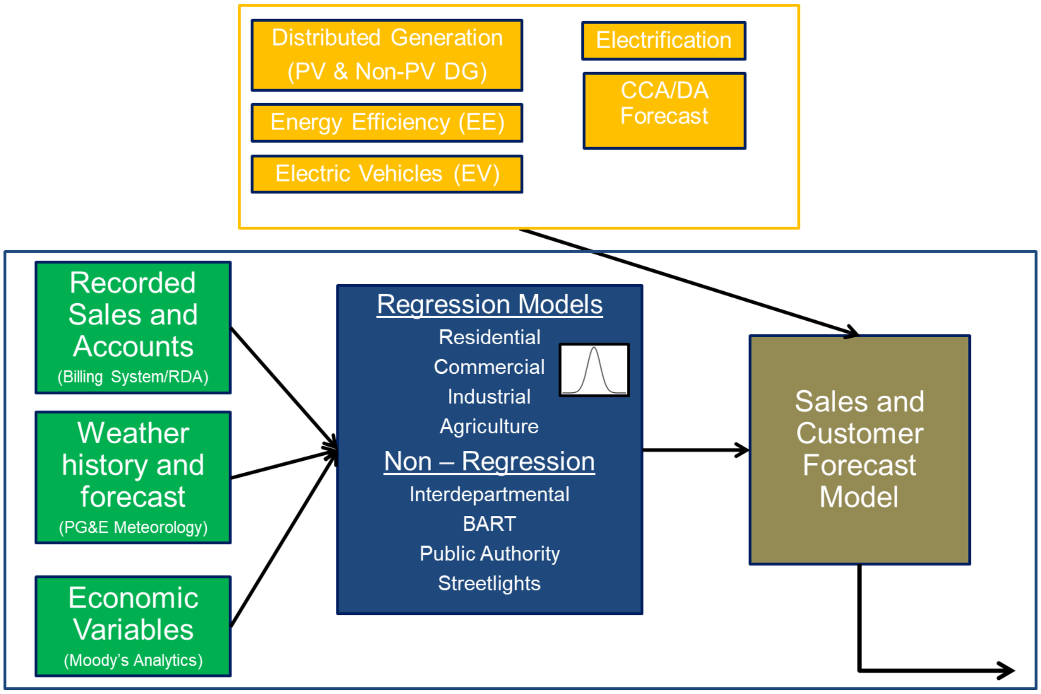
Form 2.3 provides recorded and projected customer counts by customer class. The data reported is billing data (number of bills), which is used to represent number of customers. The annual numbers reported are averages of 12 months of customer data.

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: economic/demographic, price, 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.

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: 02/15/19 Time: 14:01
Sample: 2003M06 2018M12
Included observations: 187
Convergence achieved after 20 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
PPH	-902.7452	377.5792	-2.390876	0.0179
SINGLE_FAM_PERMS_PGE	0.046562	0.013993	3.327374	0.0011
MULTI_FAM_PERMS_PGE	0.073560	0.046329	1.587755	0.1142
JAN	1739.671	1274.174	1.365332	0.1740
FEB	3187.467	1198.811	2.658858	0.0086
MAR	5039.677	1205.276	4.181348	0.0000
APR	3687.144	1205.926	3.057520	0.0026
MAY	5742.431	1202.275	4.776306	0.0000
JUN	8847.441	1179.600	7.500376	0.0000
JUL	5438.577	1179.013	4.612823	0.0000
AUG	8872.074	1178.993	7.525127	0.0000
SEP	-1019.539	1198.134	-0.850939	0.3960
OCT	-2791.726	1179.872	-2.366127	0.0191
DEC	-1525.703	1178.745	-1.294345	0.1973
JAN101112	-8641.722	2181.639	-3.961114	0.0001
SEP2017	-24074.48	3450.800	-6.976492	0.0000
AR(1)	-0.008119	0.083020	-0.097796	0.9222

R-squared	0.681012	Mean dependent var	2888.545
Adjusted R-squared	0.650990	S.D. dependent var	5621.320
S.E. of regression	3320.913	Akaike info criterion	19.14038
Sum squared resid	1.87E+09	Schwarz criterion	19.43411
Log likelihood	-1772.625	Hannan-Quinn criter.	19.25940
Durbin-Watson stat	1.863051		

Inverted AR Roots	-.01

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

JAN101112 = Month dummy to clean regression results for outlier data point.

SEP2017 = Month dummy to clean regression results for outlier data point.

Residential Usage per Account

Dependent Variable: LOG(RES_SALES_IDA/RES_ACCTS_F)
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)
Date: 02/15/19 Time: 14:01
Sample (adjusted): 2004M02 2018M12
Included observations: 179 after adjustments
Convergence achieved after 9 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.843341	0.269968	21.64456	0.0000
LOG(_2019_CWMA_RATE_REAL)	-0.033817	0.093474	-0.361779	0.7180
TERADATA_HDD_PGE	0.000474	4.83E-05	9.805682	0.0000
TERADATA_CDD_PGE	0.002045	0.000125	16.39352	0.0000
AR(1)	0.511802	0.065925	7.763373	0.0000
SAR(12)	0.957134	0.035868	26.68506	0.0000

R-squared	0.958913	Mean dependent var	6.292197
Adjusted R-squared	0.957725	S.D. dependent var	0.127428
S.E. of regression	0.026200	Akaike info criterion	-4.413147
Sum squared resid	0.118757	Schwarz criterion	-4.306307
Log likelihood	400.9766	Hannan-Quinn criter.	-4.369824
F-statistic	807.5087	Durbin-Watson stat	2.043797
Prob(F-statistic)	0.000000		

Inverted AR Roots	1.00	.86-.50i	.86+.50i	.51
	.50+.86i	.50-.86i	.00+1.00i	-.00-1.00i
	-.50+.86i	-.50-.86i	-.86+.50i	-.86-.50i
	-1.00			

CENTER_WEIGHTED_MA_RATE = Center weighted moving average residential class rate
TERADATA_HDD_PGE = Heating Degree Days (PG&E Territory)
TERADATA_CDD_PGE = Cooling Degree Days (PG&E Territory)

Commercial Accounts

Dependent Variable: D(COM_ACCTS_IDA)
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)
Date: 02/15/19 Time: 14:02
Sample: 2003M01 2018M12
Included observations: 192
Convergence achieved after 7 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	191.0725	40.68635	4.696231	0.0000
D(RES_ACCTS_F)	0.014908	0.007445	2.002449	0.0467
APR2013	-3425.905	432.8148	-7.915407	0.0000
JAN2003	-4005.817	446.1523	-8.978588	0.0000
JAN2004	4226.465	433.3833	9.752256	0.0000
MAY2013	3111.353	433.0042	7.185504	0.0000
OCT2017	190.4399	433.5718	0.439235	0.6610
AR(1)	0.058207	0.078662	0.739962	0.4603

R-squared	0.620592	Mean dependent var	239.0156
Adjusted R-squared	0.606158	S.D. dependent var	687.8185
S.E. of regression	431.6529	Akaike info criterion	15.01389
Sum squared resid	34283660	Schwarz criterion	15.14962
Log likelihood	-1433.334	Hannan-Quinn criter.	15.06887
F-statistic	42.99522	Durbin-Watson stat	1.917257
Prob(F-statistic)	0.000000		

Inverted AR Roots	.06

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.

Commercial Usage per Account

Dependent Variable: LOG(COM_SALES_IDA/COM_ACCTS_F)
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)
Date: 02/15/19 Time: 14:03
Sample: 2004M02 2018M12
Included observations: 179
Convergence achieved after 15 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.629570	0.220152	34.65588	0.0000
LOG((EMP_FIN_ACT_PGE+EMP_INFO_PGE+EMP_TOT_SVC_PGE)/EMP_TOT_PGE)	-1.623039	0.352830	-4.600057	0.0000
LOG(CWMA_RATE_REAL)	0.123203	0.088725	1.388593	0.1667
CDD_PGE_TD	0.000842	8.05E-05	10.45760	0.0000
AR(1)	0.528423	0.064443	8.199812	0.0000
SAR(12)	0.728142	0.053133	13.70403	0.0000

R-squared	0.943394	Mean dependent var	8.533409
Adjusted R-squared	0.941758	S.D. dependent var	0.072745
S.E. of regression	0.017556	Akaike info criterion	-5.213911
Sum squared resid	0.053320	Schwarz criterion	-5.107071
Log likelihood	472.6450	Hannan-Quinn criter.	-5.170588
F-statistic	576.6392	Durbin-Watson stat	2.148915
Prob(F-statistic)	0.000000		

Inverted AR Roots	.97	.84+.49i	.84-.49i	.53
	.49+.84i	.49-.84i	-.00-.97i	-.00+.97i
	-.49-.84i	-.49+.84i	-.84+.49i	-.84-.49i
	-.97			

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)
COM_RATE_REAL_CWMA = Center weighted moving average residential class rate
CDD_PGE_TD = Cooling Degree Days (PG&E Territory)

Industrial Sales

Dependent Variable: IND_SALES_IDA_2_5
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)
Date: 02/15/19 Time: 13:59
Sample: 2001M02 2018M12
Included observations: 215
Convergence achieved after 13 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.09E+09	48847856	22.28287	0.0000
GDP_MANUFACTURING_PGE	806.3813	476.9019	1.690875	0.0924
CDD_PGE_TERADATA	538254.6	153538.1	3.505675	0.0006
OCCI_DUMMY	-19159404	21339603	-0.897833	0.3704
RECESSION	-31091126	19972836	-1.556671	0.1211
JAN	11829517	7694234.	1.537452	0.1258
FEB	19880879	9981855.	1.991702	0.0478
MAR	72290973	11370575	6.357724	0.0000
APR	82902060	12317195	6.730596	0.0000
MAY	85930382	13943094	6.162935	0.0000
JUN	80775439	18450959	4.377845	0.0000
JUL	1.21E+08	23724394	5.080861	0.0000
AUG	1.54E+08	22092400	6.972255	0.0000
SEP	1.65E+08	17070108	9.647376	0.0000
OCT	1.08E+08	10739429	10.04487	0.0000
NOV	71409670	7436218.	9.602956	0.0000
AR(1)	0.788735	0.044216	17.83841	0.0000

R-squared	0.890691	Mean dependent var	1.27E+09
Adjusted R-squared	0.881858	S.D. dependent var	87379552
S.E. of regression	30033906	Akaike info criterion	37.34932
Sum squared resid	1.79E+17	Schwarz criterion	37.61584
Log likelihood	-3998.052	Hannan-Quinn criter.	37.45701
F-statistic	100.8363	Durbin-Watson stat	2.178159
Prob(F-statistic)	0.000000		

Inverted AR Roots	.79

GDP_MANUFACTURING_PGE = Gross product of manufacturing (PG&E Territory)
CDD_PGE_TERADATA = Cooling Degree Days (PG&E Territory)
JAN,FEB, MAR, APR, MAY,JUN, JUL, AUG,SEP,OCT, NOV = Monthly dummies
OCCI_DUMMY = dummy variable denoting the presence of Occidental Petroleum
RECESSION = Constructed variable to account for sales loss during the recession

Agricultural Sales

Dependent Variable: LOG(AG_SALES_IDA_2_5/AG_ACCTS_FORE)
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)
Date: 02/15/19 Time: 13:55
Sample (adjusted): 2000M11 2018M12
Included observations: 218 after adjustments
Convergence achieved after 9 iterations
MA Backcast: OFF

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.555987	1.675915	0.928440	0.3544
RAIN01	0.007778	0.010338	0.752351	0.4528
RAIN02	-0.005547	0.008985	-0.617393	0.5377
RAIN03	-0.012121	0.004645	-2.609296	0.0098
RAIN04	-0.016218	0.003982	-4.072498	0.0001
RAIN05	-0.020332	0.003973	-5.116906	0.0000
RAIN06	-0.017503	0.003418	-5.120465	0.0000
RAIN07	-0.014282	0.003476	-4.109009	0.0001
RAIN08	-0.011215	0.003265	-3.435075	0.0007
RAIN09	-0.006007	0.003214	-1.869070	0.0632
RAIN10	-0.001253	0.003045	-0.411536	0.6811
RAIN11	0.000376	0.002713	0.138592	0.8899
RAIN12	-0.001128	0.002080	-0.542017	0.5884
PDSI	-0.031271	0.009185	-3.404523	0.0008
LOG(AG_OUTPUT)	0.644063	0.169642	3.796605	0.0002
JAN	0.097793	0.050468	1.937750	0.0541
FEB	0.394901	0.070897	5.570097	0.0000
MAR	0.637380	0.079527	8.014647	0.0000
APR	0.934165	0.089286	10.46257	0.0000
MAY	1.166967	0.091446	12.76127	0.0000
JUN	1.215196	0.092057	13.20045	0.0000
JUL	1.167049	0.089933	12.97689	0.0000
AUG	1.021943	0.083870	12.18490	0.0000
SEP	0.828918	0.074281	11.15928	0.0000
OCT	0.520194	0.048286	10.77315	0.0000
NOV	0.230165	0.045806	5.024784	0.0000
AR(1)	0.838342	0.049974	16.77552	0.0000
MA(1)	-0.106073	0.092136	-1.151260	0.2511

R-squared	0.979010	Mean dependent var	8.439630
Adjusted R-squared	0.976027	S.D. dependent var	0.518639
S.E. of regression	0.080302	Akaike info criterion	-2.086645
Sum squared resid	1.225186	Schwarz criterion	-1.651939
Log likelihood	255.4443	Hannan-Quinn criter.	-1.911061
F-statistic	328.2206	Durbin-Watson stat	1.936152
Prob(F-statistic)	0.000000		

Inverted AR Roots	.84
Inverted MA Roots	.11

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 methods explained in detail in Form 6. A high level description of the forecasting method is provided below:

- **Conservation and Energy Efficiency:** PG&E combines the CEC's committed energy savings forecast with a probabilistic model applied to uncommitted savings.
- **Distributed Generation (Combustion Technologies):** PG&E develops its forecast based on historic adoption trends and assumed GHG policy constraints on future adoption.
- **Distributed Generation (Fuel Cells):** PG&E develops its forecast using a simplified Bass technology diffusion model.
- **Electric Vehicles:** PG&E develops its EV forecast using probability weighted policy-scenarios.
- **Building Electrification:** PG&E develops its Building Electrification forecast using probability weighted policy-scenarios.
- **Demand Response (Peak only):** PG&E forecasts the peak impact due to non-event based demand response programs.
- **Behind-the-Meter Storage (Peak only):** PG&E adjusts its peak for load shifting due to BTM storage. PG&E uses a Bass technology diffusion model to estimate adoption. A storage dispatch optimization model produces hourly charge/discharge profiles, which are aggregated and shaped to estimate peak impact.

a. 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.

b. 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. PG&E assumes 80 percent of EV sales register in the residential sector and 20 percent in the commercial sector.

c. Incorporating Stationary Electrification in the Forecast

This is the second 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.

d. 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 assumptions are as follows:

- Direct Access: Incorporates the DA cap increase in 2020, but assumes no additional re-opening.
- Community Choice Aggregation: A probability-weighted forecast of CCA departure for 2019 – 2030.

PG&E uses a probability-weighted approach to CCA departure for all years of its forecast. PG&E assigns probabilities to the municipalities that have demonstrated significant interest and exploratory moves towards joining or forming a CCA. Those probabilities are multiplied by the load for that city to derive an "expected value" of load departure.

e. 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^{o} F as a base, while heating degree days are calculated with a base of 60^{o} 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%

f. 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 load; transmission losses and unaccounted for energy (UFE) are calculated as 3 percent of load, per Resource Adequacy instructions.

g. Calculating Hourly Loads

PG&E uses the NELF-LT model developed by Pattern Recognition Technologies, Inc. (PRT) to forecast the 1 in 2 (expected) hourly loads. The PRT model uses a neural network load forecast engine that was developed with PG&E's historical hourly loads and temperatures. Given an hourly temperature series as input, the model will generate an hourly load forecast that reflects the role of temperatures, previous day's forecast load and the calendar effects (weekday or weekend effect) on the load.

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 publically 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, 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 again. PG&E is already losing considerable bundled load to CCAs, and PG&E expects this trend to continue 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.