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Pacific Gas and Electric Company
CEC 2017 IEPR
FORM 4
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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 2016. PG&E is presenting its sales data from the “elecfix database”, which is an analytic dataset that is continuously revised to account for rebates, rebills, and other types of billing irregularities. As such, the totals in this data set may not synch 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. Electric vehicles (EV) are shown as a separate column item although EV usage is actually embedded in customer class sales. Only residential and non-residential totals are available for recorded bundled sales data shown in 1.1b; however, PG&E does forecast bundled load by class.

In the forecast period 2017-2028, PG&E has included the effects of energy efficiency as described in the Section 3, Demand Forecast Methods, below. PG&E has also included the impacts of electric vehicles and distributed generation (DG), including rooftop solar (photovoltaic or PV). PG&E assumes there will be no reopening of direct access (DA). PG&E has developed a probabilistic departure forecast for community choice aggregation (CCA). Details on PG&E’s approach to CCA forecasting are outlined in detail in Form 4.

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 are replicated in Form 1.2 from 1.1b. PG&E has no reason, at this time, to expect a material change in departing municipal load. Losses are distribution, transmission, and unaccounted for energy for bundled, DA, and CCA customers (losses associated with BART loads are not included.) Column L, uncommitted energy efficiency impacts are described below. Column M does not include the effects of uncommitted energy efficiency (unmitigated for EE) but does include load reductions for customer self-generation.

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, we are 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 and incremental customer self-generation programs in the period 2015 through 2026 are included in the forecast data.

Form 1.4 Distribution Area Coincident Peak Demand

DA / CCA losses are assumed to be 3.6 percent for distribution and 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, except for the 1 in 40 scenario for which we currently do not have a multiplier. 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 2015 and 2016 are consistent with the distribution loss factor algorithms used in the Settlements process. Forecasted distribution losses for 2017 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 percent and 0.5 percent, 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 hourly load for various local areas; the sum of these local area hourly loads does not equal the Total System Load provided, as there is load within PG&E's total system area not represented in any one local area.

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

II. Forecast Input Assumptions

Form 2.1 PG&E Planning Area Economic and Demographic Inputs

Inputs are drawn from Moody's Analytics December 2016 baseline projections for PG&E's service area economy.

Form 2.2 Electricity Rate Forecast

The 2017 average rates are derived from the 2017 Annual Electric True-Up. Beyond 2017, 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

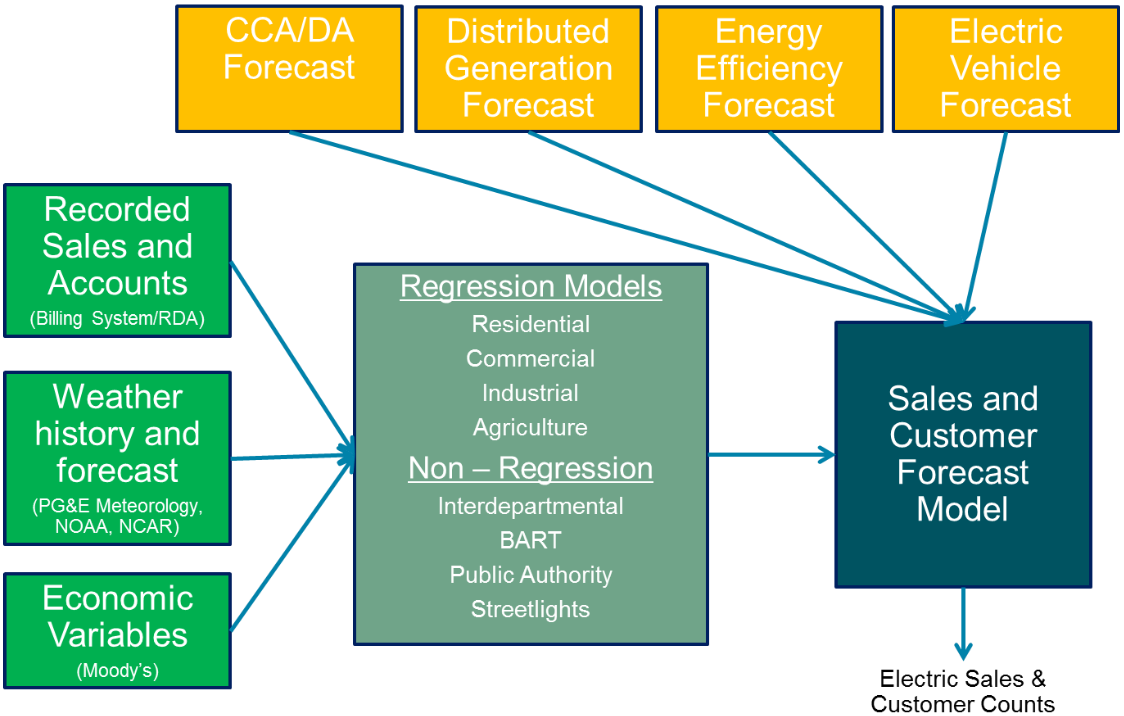
Form 2.3 provides recorded and projected customer counts by customer class. The data reported is billing data (number of bills), which is used to represent number of customers. The annual numbers reported are averages of 12 months of customer data.

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, and community choice aggregation. PG&E's process for developing forecasts of energy sales is shown in Figure 1.

Traditionally, PG&E used a similar time series approach to develop the coincident system peak demand (peak) forecast. However, rapid expansion of behind-the-meter solar PV has resulted in observed shifts in peak times to later hours in the day. 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). Resale (wholesale) customer service, which at one time constituted a material level of demand, now amounts to just a very small amount of imbalance power.

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 classes energy forecast are shown below (pp. 7-12):

Residential Accounts

Dependent Variable: D(RES_ACCTS_IDA)
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)
Date: 01/26/17 Time: 10:52
Sample: 2003M06 2016M10
Included observations: 161
Convergence achieved after 18 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
PPH	-1141.426	326.4436	-3.496549	0.0006
SINGLE_FAM_PERMS_PGE	0.051369	0.011693	4.392979	0.0000
MULTI_FAM_PERMS_PGE	0.050830	0.045599	1.114705	0.2668
JAN	2294.221	1132.870	2.025140	0.0447
FEB	4638.271	1028.364	4.510339	0.0000
MAR	5532.770	1040.243	5.318729	0.0000
APR	4078.717	1041.988	3.914362	0.0001
MAY	6661.745	1037.841	6.418851	0.0000
JUN	9620.038	1014.292	9.484481	0.0000
JUL	6232.327	1012.113	6.157736	0.0000
AUG	10040.12	1010.502	9.935775	0.0000
SEP	-96.68775	1008.559	-0.095867	0.9238
OCT	-3425.547	1003.336	-3.414158	0.0008
NOV	1776.961	1061.036	1.674742	0.0961
JAN101112	-7822.503	1742.581	-4.489034	0.0000
AR(1)	-0.073862	0.084294	-0.876237	0.3824

R-squared	0.757053	Mean dependent var	2937.770
Adjusted R-squared	0.731921	S.D. dependent var	5026.572
S.E. of regression	2602.576	Akaike info criterion	18.66048
Sum squared resid	9.82E+08	Schwarz criterion	18.96670
Log likelihood	-1486.168	Hannan-Quinn criter.	18.78482
Durbin-Watson stat	1.954063		

Inverted AR Roots	-.07

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.

Residential Usage per Account

Dependent Variable: LOG(RES_SALES_IDA/RES_ACCTS_IDA_F)
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)
Date: 01/31/17 Time: 16:03
Sample (adjusted): 2004M02 2016M10
Included observations: 153 after adjustments
Convergence achieved after 10 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.858801	0.160004	36.61658	0.0000
LOG(CENTER_WEIGHTED_MA_RATE)	-0.109662	0.083716	-1.309921	0.1923
TERADATA_HDD_PGE	0.000473	4.66E-05	10.15945	0.0000
TERADATA_CDD_PGE	0.001921	0.000121	15.89980	0.0000
AR(1)	0.478207	0.072891	6.560601	0.0000
SAR(12)	0.943644	0.038108	24.76204	0.0000

R-squared	0.959476	Mean dependent var	6.308821
Adjusted R-squared	0.958098	S.D. dependent var	0.114909
S.E. of regression	0.023522	Akaike info criterion	-4.623351
Sum squared resid	0.081332	Schwarz criterion	-4.504510
Log likelihood	359.6863	Hannan-Quinn criter.	-4.575075
F-statistic	696.1001	Durbin-Watson stat	1.954722
Prob(F-statistic)	0.000000		

Inverted AR Roots	1.00	.86-.50i	.86+.50i	.50+.86i
	.50-.86i	.48	.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: 02/03/17 Time: 10:05
Sample: 2003M01 2016M10
Included observations: 166
Convergence achieved after 14 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	149.0753	49.66051	3.001887	0.0031
D(RES_ACCTS_IDA_F)	0.034379	0.008008	4.293237	0.0000
APR2013	-3678.150	495.8922	-7.417238	0.0000
JAN2004	4410.323	498.7657	8.842473	0.0000
JAN2003	-3240.718	540.6231	-5.994413	0.0000
AR(1)	0.104969	0.083025	1.264308	0.2080

R-squared	0.561046	Mean dependent var	233.9458
Adjusted R-squared	0.547329	S.D. dependent var	738.6000
S.E. of regression	496.9364	Akaike info criterion	15.29028
Sum squared resid	39511331	Schwarz criterion	15.40276
Log likelihood	-1263.093	Hannan-Quinn criter.	15.33593
F-statistic	40.90056	Durbin-Watson stat	1.938710
Prob(F-statistic)	0.000000		

Inverted AR Roots	.10

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_IDA_F)
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)
Date: 02/07/17 Time: 15:20
Sample (adjusted): 2004M02 2016M10
Included observations: 153 after adjustments
Convergence achieved after 11 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.756018	0.156131	49.67622	0.0000
LOG((EMP_FIN_ACT_PGE+EMP_INFO_PGE+EMP_TOT_SVC_PGE)/EMP_TOT_PGE)	-1.085327	0.276605	-3.923738	0.0001
LOG(COM_RATE_REAL_CWMA)	-0.009224	0.077168	-0.119534	0.9050
CDD_PGE_TD	0.000850	8.73E-05	9.746234	0.0000
AR(1)	0.385285	0.077491	4.971993	0.0000
SAR(12)	0.711318	0.060315	11.79346	0.0000

R-squared	0.929267	Mean dependent var	8.546324
Adjusted R-squared	0.926861	S.D. dependent var	0.064524
S.E. of regression	0.017450	Akaike info criterion	-5.220526
Sum squared resid	0.044762	Schwarz criterion	-5.101686
Log likelihood	405.3703	Hannan-Quinn criter.	-5.172251
F-statistic	386.2457	Durbin-Watson stat	2.051171
Prob(F-statistic)	0.000000		

Inverted AR Roots	.97	.84+.49i	.84-.49i	.49+.84i
	.49-.84i	.39	.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
Method: ARMA Conditional Least Squares (Marquardt - EViews legacy)
Date: 02/14/17 Time: 07:15
Sample: 2001M02 2016M10
Included observations: 189
Convergence achieved after 13 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.02E+09	57560010	17.70173	0.0000
GDP_MANUFACTURING_PGE	1616.394	602.9439	2.680836	0.0081
CDD_PGE_TERADATA	558505.7	168487.5	3.314820	0.0011
OCCI_DUMMY	-20462445	21636298	-0.945746	0.3456
RECESSION	-39106667	19961914	-1.959064	0.0517
JAN	11002743	8460098.	1.300546	0.1952
FEB	23100397	10927853	2.113901	0.0360
MAR	69976007	12424288	5.632195	0.0000
APR	83720309	13454276	6.222580	0.0000
MAY	85610014	15268614	5.606928	0.0000
JUN	81989691	19945060	4.110777	0.0001
JUL	1.20E+08	25376219	4.742275	0.0000
AUG	1.50E+08	23855045	6.287401	0.0000
SEP	1.64E+08	18789676	8.741177	0.0000
OCT	1.03E+08	12002168	8.576977	0.0000
NOV	70133685	8371092.	8.378081	0.0000
AR(1)	0.770630	0.049963	15.42399	0.0000

R-squared	0.889925	Mean dependent var	1.27E+09
Adjusted R-squared	0.879686	S.D. dependent var	88643762
S.E. of regression	30747253	Akaike info criterion	37.40614
Sum squared resid	1.63E+17	Schwarz criterion	37.69773
Log likelihood	-3517.880	Hannan-Quinn criter.	37.52427
F-statistic	86.91110	Durbin-Watson stat	2.048599
Prob(F-statistic)	0.000000		

Inverted AR Roots	.77

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/AG_ACCTS_FORE_2017)
Method: Least Squares
Date: 02/08/17 Time: 16:14
Sample (adjusted): 2001M01 2016M10
Included observations: 190 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-7.796201	0.349489	-22.30745	0.0000
LOG(AG_RATE_IDA_RATEFORE_CWM)	-0.339254	0.058845	-5.765237	0.0000
LOG(AG_OUTPUT)	0.018750	0.040569	0.462175	0.6445
LOG(AG_SALES_IDA(-1))	0.809065	0.055737	14.51575	0.0000
LOG(AG_SALES_IDA(-2))	-0.115563	0.053341	-2.166508	0.0317
LOG(AG_SALES_IDA(-12))	0.087352	0.033465	2.610239	0.0099
RAIN_COMPOSITE	-0.054496	0.004636	-11.75465	0.0000
CDD_PGE_TERADATA	0.000824	0.000387	2.128803	0.0347
FEB	0.087767	0.028288	3.102668	0.0022
MAR	0.220801	0.034641	6.373989	0.0000
APR	0.256786	0.042135	6.094360	0.0000
MAY	0.230111	0.047910	4.802962	0.0000
JUN	0.142373	0.054595	2.607814	0.0099
JUL	0.060903	0.061806	0.985393	0.3258
AUG	-0.070568	0.056801	-1.242376	0.2158
SEP	-0.148331	0.044633	-3.323337	0.0011
OCT	-0.152012	0.031353	-4.848369	0.0000
NOV	-0.186122	0.026957	-6.904310	0.0000
DEC	-0.166743	0.025376	-6.570796	0.0000

R-squared	0.986779	Mean dependent var	8.451983
Adjusted R-squared	0.985387	S.D. dependent var	0.513344
S.E. of regression	0.062054	Akaike info criterion	-2.626975
Sum squared resid	0.658475	Schwarz criterion	-2.302273
Log likelihood	268.5626	Hannan-Quinn criter.	-2.495443
F-statistic	709.0595	Durbin-Watson stat	2.130482
Prob(F-statistic)	0.000000		

C = Constant

AG_RATE_IDA_RATEFORE_CWM = Ag class average real rates (Center-Weighted Moving Avg.)

AG_OUTPUT = PG&E service area Ag GDP (Moody’s Analytics)

AG_SALES_IDA(-1) = Agricultural sales 1 month lag

AG_SALES_IDA(-2) = Agricultural sales 2 months lag

AG_SALES_IDA(-12) = Agricultural sales 12 months lag

RAIN_COMPOSITE = Average rainfall observed in Sacramento and Fresno

CDD_PGE_TERADATA = Cooling Degree Days (PG&E Territory)

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

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 is also incorporated into the forecast. For most of these policies, PG&E's approach is to compare the level of the program in the existing data with the program levels that are anticipated in the future, and to adjust the forecast accordingly. The assumptions are derived as follows:

- Conservation and Energy Efficiency: PG&E internal analysis (see Form 6 for details)
- Distributed Generation: PG&E internal analysis (see Form 6 for details).
- Electric Vehicles: PG&E internal analysis. The EV forecast is based on the ZEV Mandate and other statewide goals for various levels of EV adoption. The forecast assumes that the state will exceed the ZEV Mandate, but may fall short of meeting Governor Brown's goal of having 1.5 million ZEVs on the road by 2025. This forecast is consistent with the recent EV registration trends that PG&E has seen in its territory.
- Demand Response (Peak only): PG&E internal analysis (see notes for Form 6)
- Behind-the-Meter Storage (Peak only): New to the peak forecast, PG&E adjusts its peak for load shifting due to BTM storage. PG&E uses an adoption model framework (Bass-Diffusion based adoption calculation) with storage dispatch optimization functionality, which calculates adoption of BTM storage and hourly aggregate charge/discharge profile.

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. 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: Assumes no re-opening of DA
- Community Choice Aggregation: A probabilistic forecast of CCA departure for 2017 – 2028.

PG&E uses a probabilistic 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.

d. 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%	7%
Eureka	1%	1%
Oakland	14%	11%

San Jose	19%	16%
San Rafael	3%	2%
Salinas	7%	5%
Livermore	10%	10%
Paso Robles	2%	2%

e. Calculating Losses

Historical losses can be estimated by calculating the difference between metered sales and retail generation. PG&E has included this calculation for years 2000 through 2016 on Form 1.2. 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.

f. 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 decline in 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 we expect 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 2020, the system coincident peak hour is assumed to be 8pm, predominantly due to the rapid expansion of BTM PV. EV charging is a relatively small contribution to peak increases, and mostly offset by BTM Storage discharging during peak hours.

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