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Central Coast Community Energy

2025 Integrated Energy Policy Report

Electricity Demand Forecast Filling

Form 4 – Demand Forecast Methodology

MONTHLY TOTAL ENERGY FORECAST

TEA utilizes a combination of weather variables, economic variables, and monthly constants in forecasting Central Coast Community Energy (CCCE) monthly total energy. The sections below describe the data collection and model selection process for each forecasting model.

DEPENDENT VARIABLES

Historical Load

CCCE provided historical hourly rate class load for January 2020 – December 2024. This data was aggregated to the monthly level for each rate class, separated for CCCE customers within PG&E or SCE's service territory

INDEPENDENT VARIABLES

Weather Variables

7 years of historical temperature data was collected from DTN Weather, measured at the Monterey Regional Airport from January 2018 – December 2024. Temperature data was collected at the hourly level and summarized to the monthly level for the variables listed below. Degree days for each variable utilized a base temperature of 65 degrees Fahrenheit.

- **CDDSUM**: The sum of cooling degree-days base 65 observed across a month.
- **HDDSUM**: The sum of heating degree-days base 65 observed across a month.
- **CDDMAX**: The maximum of cooling degree-days base 65 observed in a month.
- **HDDMAX**: The maximum of heating degree-days base 65 observed in a month.

A 50/50 normalized weather forecast was developed for future years informed by the 7 years of hourly historical temperature data. This temperature forecast was developed from the hourly data using the rank and median method. This methodology mimics the rank and average method described in Itron's Energy Forecasting White Paper[1], using historical medians instead of historical averages for ranked days.

Economic Variables

Annual economic data was collected for applicable counties from Woods & Poole's 2024 Complete Economic and Demographic Data Source (Woods & Poole). The Woods & Poole economic data included history beginning in 1970, and forecasts extending from 2024 to 2060. The figure below provides an overview of counties included in the economic data used. For CCCE PG&E load, economic data for all three counties were aggregated before being evaluated as predictor variables.

IOU Service Territory	County
PG&E	Monterey, CA
	San Benito, CA
	Santa Cruz, CA
SCE	Santa Barbara, CA

[1] https://na.itron.com/o/commerce-media/accounts/-1/attachments/3827660

Nine different economic variables were evaluated in the regression process, listed below:

- **TotalPopulation**: Total County population (in thousands).
- **TotalEmployment**: Total County employment (in thousands of jobs).
- **TotalPersonalIncome**: Total personal income for all County residents (in millions of 2017 dollars).
- **GrossRegionalProduct**: Value of goods and services produced in the County (in millions of 2017 dollars).
- **NumberOfHouseholds**: Number of households within the County (in thousands).
- **TotalRetailSales:** Total retail sales within the County (in millions of 2017 dollars).
- **Woods&PooleWealthIndex:** Relative wealth index, weighting secondary income more heavily.
- **IncomePerCapita:** Income per capita within the County (in millions of 2017 dollars).
- **MeanHouseholdIncome:** Mean household income within the County (in millions of 2017 dollars).

Month Constants

Constant variables were utilized for each month of the year, allowing the seasonal models to consider different regression constants depending on the month being predicted. Each of these variables contained a value of either one or zero. A value of one is observed only when predicting months corresponding to the month variable. For example, when predicting February 2026, the constant variable 'Month2' will have a value of one, while all other month variables will have a value of zero.

MODEL SELECTION

After collecting the historical data for all dependent and independent variables, each possible combination of historical weather and economic features were then evaluated for use in the total energy regression models. Combinations were restricted to include at least two weather variables and only one economic variable. This limitation was done to avoid collinearity between multiple weather or economic variables. After evaluating each combination of variables, the following steps were used to select the ideal model:

1. **Positive Economic Coefficient:** Possible models were filtered to only include those with positive regression coefficients for the economic variable. This was done to ensure the selected model is assuming a positive relationship between economic growth (or decline) and load growth (or decline).
2. **P-value Filtering:** Possible models were filtered to only include those with the minimum number of independent variables having a p-value greater than 0.05. This was done to ensure the selected model contains the maximum amount of statistically significant predictors of total energy, while avoiding non-significant predictors.
3. **Adjusted R^2 selection:** After filtering the possible models based on the economic coefficient and p-values, the selected model was then determine based on the highest adjusted R^2 value.

The selected regression model for total energy was then used to predict future load, using normalized weather and economic projections described above.

MONTHLY PEAK DEMAND FORECAST

Historical monthly load factors were calculated using the hourly history provided by CCCE. Forecasted monthly peak demand was then derived using the average historical load factors for each month, and the predicted monthly total energy. This peak demand forecast was aggregated for CCCE customers within PG&E and SCE service territories. System coincident peak demand was then calculated based on the historical coincidence factor between CCCE's PG&E and SCE non-coincident peak demand, and CCCE system coincident peak.

HOURLY FORECAST

CCCE's PG&E and SCE hourly load data was collected for the period January 2020 – December 2024. Hourly historical weather data at the Monterey Regional Airport was collected from DTN weather for January 2018 – December 2024. Seven years of historical weather data was then used to calculate hourly normalized weather using the rank and median method for the forecast horizon.

A non-linear machine learning model (GBM) was trained to predict load values given the historical weather data, actual system load, and time series features including hour of the day, month, and day of the week. The trained model was then used to predict hourly system load using the normalized weather forecast.

The hourly forecasted load was then fitted to the monthly total energy and peak demand projections described in the previous section. This was done to ensure congruence between the two predictions, since this hourly model has no feature which incorporates long-term economic growth.

ADDITIONAL ADJUSTMENTS OR CONSIDERATIONS

NEW MASS ENROLLMENTS

The onboarding of San Luis Obispo County and the City of Atascadero were incorporated into the forecast beginning in 2025. Historical load data for these two mass enrollments were collected from CCCE. This included 2022 history for customers in San Luis Obispo County and 2021 history for Atascadero. Because only one year of historical load was available, the forecast for both mass enrollments was held constant year-over-year. The rate class breakdown of new mass enrollment load was assumed to match the current breakdown of CCCE PG&E customer-class load, due to data availability.

ELECTRIC VEHICLE CHARGING LOAD

Electrification in the transportation sector is expected to continue driving load growth in residential and commercial sectors. The following data and assumptions were used to forecast EV load:

- To forecast future light-duty electric vehicle charging impacts, California state-level projections for vehicle adoption and economic projections were collected from S&P and Woods & Poole's 2024 Complete Economic and Demographic Data Source, respectively. The forecasted adoption rate of electric vehicles (EVs) was calculated as a function of these two data sources. This forecasted adoption rate was incremental to the CCCE customer's existing electric vehicles as of 2024.

- Since all county residents are not CCCE customers, the county-level electric vehicle adoption was scaled down. This scaling was based on the ratio of CCCE residential customers to total households in Monterey, San Benito, Santa Cruz, Santa Barbara, and San Luis Obispo Counties.
- Hourly charging load per-vehicle was projected using the National Renewable Energy Laboratory's Electric Vehicle Infrastructure Projection Tool[2]. This tool creates an hourly weekday and weekend EV charging load profile based on a given number of EVs. This per-vehicle hourly charging forecast was then multiplied by the projected number of vehicles to derive forecasted annual electric vehicle charging load.

ROFFTOP SOLAR GENERATION

The National Renewable Energy Laboratory's (NREL) ReEDS model was utilized to estimate future rooftop solar adoption and its impact on load. The 2024 Standard Scenarios – Base Case was utilized from NREL's published ReEDS model projections. These forecasts provide annual rooftop solar projections by region with the United States.

These regional projections were scaled down to the sub-region of CCCE's service area using the ratio of CCCE residential customers relative to the number of households within the applicable region.

A fixed-axis rooftop PV generation profile was created using NREL's PVWatts model. This profile, combined with the scaled adoption forecast, was used to project reductions in net load due to behind-the-meter residential solar systems.

DISTRIBUTION LOSSES

Up to this point in the process, all loads forecasted are wholesale loads. Monthly loss factors were applied to the load forecasts to develop a projected retail load, inclusive of distribution losses.

Hourly retail and wholesale load data for 2024 was collected and the percent difference between the two load volumes was calculated to determine hourly distribution loss factors. These losses were separated by residential and non-residential CCCE customers within PG&E or SCE service territory. Historical hourly loss factors were then averaged by month. The monthly loss factors below were applied to the monthly total energy forecast, to determine annual total energy including distribution losses.

[2] https://afdc.energy.gov/evi-x-toolbox#/evi-pro-loads

PG&E Distribution Losses		
Month	**Residential**	**Non-Residential**
1	6.8%	5.5%
2	6.7%	5.4%
3	6.6%	5.3%
4	6.6%	5.4%
5	6.8%	5.5%
6	7.2%	6.0%
7	7.8%	6.6%
8	7.4%	6.3%
9	7.2%	6.1%
10	7.0%	5.9%
11	6.8%	5.7%
12	6.8%	5.8%

SCE Distribution Losses		
Month	**Residential**	**Non-Residential**
1	5.9%	5.6%
2	5.9%	5.6%
3	5.6%	5.3%
4	5.6%	5.3%
5	5.6%	5.3%
6	6.4%	6.1%
7	7.4%	7.0%
8	7.2%	6.8%
9	7.0%	6.5%
10	6.3%	6.0%
11	5.8%	5.5%
12	5.9%	5.6%

Similar to total energy, peak demand projections are wholesale loads, excluding losses. To determine the impact of losses in peak demand, historical losses for residential and non-residential customers were calculated during the coincident peak hour in 2024. Distribution loss impacts on the peak demand forecast were then calculated using the 2024 historical losses observed during coincident peak demand.

Peak Demand Distribution losses	
Residential	**Non-Residential**
8.63%	7.60%