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SCE 2021 IEPR Sales and Customer Forecast Work Paper

Southern California Edison

1) Introduction

SCE uses econometric models to develop its retail sales forecast – a forecast of monthly retail electricity sales (billed recorded sales measured at the customer meter) by customer class. Retail sales are final sales to bundled, Direct Access (DA), and Community Choice Aggregate (CCA) customers. DA and CCA sales are subtracted from the retail sales forecast in order to derive to the forecast of SCE bundled customer sales. Retail sales exclude sales to public power customers, contractual sales, resale city sales, municipal departing load and inter-changes with other utilities.

The retail sales forecast represents the sum of sales in six customer classes: residential, commercial, industrial, public authority, agriculture and street lighting. Each customer class forecast is itself the product of two separate forecasts: a forecast of electricity consumption and a forecast of the number of customers[1]. Customer class data are used because they have been defined in a consistent manner throughout the sample period used in the econometric estimation.

In addition to the categorization by customer class, residential sales are further modeled and forecasted according to geographical region. The SCE service area encompasses several distinct climate zones. Accordingly, we model residential electricity consumption in part to capture regional variation in the weather/consumption relationship.

The electricity consumption per customer or per square foot forecasts are produced by statistical models that are based upon measured historical relationships between electricity consumption and various economic factors that are thought to influence electricity consumption. The estimation procedure used to construct these statistical models is ordinary least squares (OLS). Another set of econometric equations are used to forecast customers by customer class (in most cases customer additions are modeled (the change in the number of customers in the current month and the previous month) and converted into a forecast of total customers).

The regression equations, combined with forecasts of various economic drivers, such as employment and output, along with normal weather conditions and normal number of days billed, are used in combination to predict sales by customer class. Model-generated forecasts may be modified based on current trends, judgment, and events that are not specifically modeled in the equations.

For this preliminary 2022 ERRA filing, the forecast was developed in Q4, 2020 using actual load history through August 2020.

Direct Access and Community Choice Aggregate

As a result of SB 237 passed in 2018 and D.19-05-043 issued in 2019, SCE's forecast reflects the lifting of the existing DA cap starting in 2021 The forecast reflects a one-year increase in the cap. However, due to the impact of COVID-19 on commercial and industrial energy demand, DA load is not expected to reach the new cap level until 2022. SCE had its first departing Community Choice Aggregate (CCA) load starting in May 2015 in the form of Lancaster Choice Energy (LCE) followed by Apple Valley Choice Energy (AVCE) and Pico Rivera Innovative Municipal Energy (PRIME) phase one, both of which started service in 2017, and Clean Power Alliance (CPA) phases one and two, PRIME phase two, San Jacinto Power (SJP) and Rancho Mirage Energy Authority

[1] Electricity usage of residential, agriculture, commercial, and streetlights service accounts is forecasted by consumption per customers. Electricity usage of industrial and public authority (OPA) service accounts is forecasted by usage per square footage.

(RMEA) in 2018. CPA added phases three and four in 2019. In 2020, Desert Community Energy (DCE), Western Community Energy (WCE), CPA phase five, and initial municipal and residential phases for Baldwin Park Resident Owned Utility District (BPROUD) and Pomona Choice Energy (PCE) began operations In 2021, CCA operations will begin for the nonresidential phases of BPROUD and PCE as well as the Santa Barbara Clean Energy (SBCE) (residential and municipal only) and Central Coast Community Energy's (3CE)'s CCA operations in SCE's Santa Barbara County service territory (all accounts). For 2022, SBCE's nonresidential phase, Orange County Power Authority (OCPA) (all accounts in two phases), and Energy for Palmdale Independent Choice (EPIC) will start services. Starting in 2023, SCE incorporates a probabilistic model to produce a Monte Carlo simulation to forecast additional CCA load departure. SCE has incorporated its best estimate of the migrating CCA load to this forecast based on the best information SCE had received at the time that this forecast was made. For its 2022 Resource Adequacy (RA) and ERRA forecasts, SCE used hourly historical data for forecasting loads for existing CCAs through the end of 2020.

2) Forecast Assumptions and Drivers

The underlying assumptions regarding the economy, weather, electricity prices, conservation, self-generation, and transportation electrification are all significant factors affecting the sales forecast. Each of these important variables is discussed briefly below.

Employment

Changes in employment is often a source of explanatory power in measuring and predicting variation in non-residential electricity consumption. Changes in employment cause both seasonal variations in electricity consumption and changes in the long-term rate of growth in consumption over the forecast period. Only government employment is used an explanatory variable to model public authority (federal, state, or local government) customer class electricity sales.

The short-run elasticity value for the impact of government employment growth on the electricity consumption is 4.3.

Weather

SCE updated typical year weather assumptions based on historical trend analysis using historical temperature data from 1962 to 2019. SCE then estimated CDDs and HDDs for 2021 and beyond based on its updated typical year weather assumptions. Normal weather or typical year weather conditions are assumed throughout the forecast period. For purposes of model estimation and forecasting, daily actual and normal temperature data are transformed into monthly cooling degree days (CDD), that is the summer season from April to October, and heating degree days (HDD), meaning the winter season from November to March. A base temperature of 70 degrees F is used to calculate monthly cooling degree days and a base temperature of 65 degrees F is used to calculate monthly heating degree days. The CDD and HDD variables used in model estimation are based on daily temperatures that are a weighted average of 10 stations located in the SCE service area. The station locations are Ontario, Thermal, Long Beach, Riverside, Burbank, Santa Ana, Oxnard, Fresno, Lancaster and Los Angeles International Airport.

An important aspect in the calculation of CDD/HDD is the weights attached to the weather stations. The weather station weights reflect the historical geographical customer distribution. SCE customer growth is increasing faster in the areas experiencing higher temperatures in the summer and lower temperatures in the winter and thereby have a higher frequency of cooling and heating appliances.

In the residential models, the stations selected represent temperatures in the counties served by SCE. For example, the residential Orange County model uses a customer weighted average of temperatures recorded by the Santa Ana, Long Beach and Riverside weather stations. The non-residential identical sales models are estimated with customer and appliance weighted CDDs/HDDs. Commercial, industrial, and public authority sales models are estimated using only the customer adjusted CDDs/HDDs.

Since normal weather is assumed throughout the forecast, weather variation generates a seasonal pattern to electricity use but has only a small influence on the trend. More detail on weather normalization is provided below.

Billing Days

We define billing days as the sum of the number of calendar days between meter reads for each of the meter read cycles. There are typically 21 meter reading cycles to a month. The number of days for which a customer is billed can vary depending upon meter reading schedules in a month and the number of holidays and weekend days in a month. Recorded sales will therefore vary with the number of days billed. The average number of billing days in a month turns out to be a very important source of explanatory power in all the electricity use models. For purposes of the forecast, we assume the historical average number of billing days in each month. Like weather, billing days explains variation in use over the months in a year but does not contribute to trend growth in electricity consumption.

Electricity Prices

It is typically difficult to estimate a statistically significant relationship between changes in electricity consumption and changes in electricity prices. There are a number of reasons for this. First, electricity prices are regulated and therefore may vary only infrequently. Second, price signals between electric utilities and consumers can be obscured by lags in the transmission of price information and the complexities inherent in tariff structures. Finally, electricity consumption is considered to be a necessity good, which means that consumption is relatively unresponsive to changes in price, at least in the short run. In other words, the short-run residential price elasticity of demand, as derived from our forecast models, is generally in the range of --0.7 to -0.04. For purposes of model estimation, electricity prices are derived as monthly utility revenue divided by kWh consumption (i.e., unit revenue prices) and deflated by a consumer purchasing index in order to express rates in constant dollars.

Real Output

Real output serves much the same purpose in the residential electricity consumption model that employment does in the commercial and industrial electricity consumption models: Changes in output per capita explain a significant amount of the variation in residential electricity consumption that is due to changes in economic conditions. Although changes in real output explain some of the seasonal variation in residential electricity consumption, it is really a major determinant of the long-run growth trend in residential electricity consumption. Real output elasticities are typically in range of 0.6 to 2.8. SCE uses historical and forecast real output per capita by metropolitan statistical area from Moody's Analytics in our regional residential OLS forecasting models. In the case of Riverside and San Bernardino counties, MA's combined Inland Empire MSA real output forecast was divided using a 10-year compound average growth rate based on historical county employment data obtained from CA EDD.

Self-Generation

The forecast of customer on-site bypass self-generation is calculated from two lists of customers operating generating systems interconnected to the SCE grid for the purpose of meeting their own energy requirements: a thermal list and a solar list. Both customer lists identify those customers that have behind-the-meter systems on-line, under construction or current plans to install. The description of each facility includes designation of customer class, nameplate capacity in kilowatts (KW), probable bypass KW, capacity factor and on-line date. Separate forecasts are developed for thermal and solar/renewable systems and then combined for use in the sale forecast. Both lists are used to estimate annual energy production by customer class, which is allocated to the months in the year.

For thermal generation, the annual energy is calculated using the bypass capacity and a high capacity factor for all hours of the year. The annual energy is distributed to the months using a thermal load shape based on typical TOU-8 customer load shape, modified to be fully online during the on-peak periods from June into October of each year. The hourly loads are summed by month in order to produce a thermal by-pass consumption variable.

There were approximately 385,410 operational residential and non-residential behind-the-meter solar systems at the end of 2020 ranging in size from 1KW to more than 2,000 KW within the SCE service area. For the solar generation, the annual energy is calculated using the capacity factors. The capacity factors reflect the updates from the 2020 California Energy Commission capacity factor study, which takes into account system orientation of NEM interconnection data. An average capacity factor for SCE territory was used. Annual energy is distributed to the months of the year using a load shape based on hourly distribution. The monthly thermal and solar by-pass variables are summed for a single by-pass variable suitable for inclusion in the sales forecasting models.

Solar Photovoltaic

SCE models the residential adoption of solar photovoltaic through a generalized Bass diffusion model.[2] The Bass diffusion model is a standard technology adoption model originally developed in 1969.[3] The SCE model uses percentage changes in the price-per-Watt-AC of installation, adjusted for the Federal Investment Tax Credit, as its explanatory variable. Bloomberg New Energy Finance (BNEF) provided SCE's historical and forecast solar installation price series from 2010-2030.[4] The compound monthly growth rate was used to extend this series back to 2000. Residential solar photovoltaic adoption history comes from SCE's internal net energy meter (NEM) database. Non-residential solar photovoltaic adoption is modeled using a simulated Bass Diffusion model calibrated to the historical installs.

As the models are essentially a regression, expected policy changes in the future that are not reflected in the history require post-model adjustment. Additional estimates were performed to account for future PV installations in compliance with Title 24 policies for SF new construction solar PV which started in 2020. SCE also incorporates additional future NEM 3.0 impact adjustment. SCE assumes that the compensation rate for the net export solar energy back to the grid will be reduced by half under future NEM 3.0. As a result,

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[2] Bass, Frank M., Trichy V. Krishnan, Dipak C. Jain. "Why the Bass Model Fits Without Decision Variables." Marketing Science. Vol. 13, No. 3, Summer 1994.

[3] Bass, Frank. "A New Product Growth for Model Consumer Durables." Management Science. Vol. 15, Issue 5, 1969.

[4] 1H 2020 U.S. PV Market Outlook data set, Bloomberg New Energy Finance, April 8th 2020.

the annual incremental solar adoptions are reduced by 17% due to NEM 3.0 from years 2023 to 2030. Further post-model adjustments were made to incorporate impacts due to COVID-19. The forecasted COVID impacts were applied midway through 2021.

Behind-The-Meter (BTM) Energy Storage

SCE forecasts adoption of paired solar PV and energy storage systems as well as standalone energy storage systems for residential and non-residential customers in the SCE service territory. SCE employs the System Advisor Model (SAM) by the National Energy Laboratory (NREL) to generate the key economic analysis or bill savings analysis for residential energy storage systems. The major inputs of SAM are considered such as hourly electric loads, rates, incentives, and system costs. SCE then applies SCE's internal analysis to estimate the annual adoptions. First, SCE converts the bill savings estimates from the SAM model into the maximum market potential based on SCE's internal analysis. Next, SCE runs a Bass Diffusion Model with estimated maximum market potential and other specified parameters to produce an annual adoption forecast. Additional installations are incorporated in the forecast based on the SGIP Equity Resiliency Incentive Program future incentive dollars and historical application data. SCE aggregates the adoption forecasts by two major categories: the paired systems and the stand-alone systems. Non-residential energy storage systems are modeled separately with trend analyses based on historical adoption. SCE specifies the representative storage system size for each customer group based on historical installation statistics. Short-term post-model reductions to the non-residential energy storage forecast due to COVID-19 were applied to 2021, based on external vendor outlooks and observed impacts in 2020. The SAM model simulates 8760 hourly storage system dispatch profile for residential customers, and the 2019 SGIP Advanced Energy Storage Impact Evaluation was used to produce non-residential paired and standalone energy storage charge/discharge profiles. SCE then aggregated all groups together to form a system level energy storage 8760 profile.

Transportation Electrification

SCE forecasts future transportation electrification (TE) load growth for both light duty vehicle (LDV) load and non-LDV load. Non-LDV load includes medium, heavy duty, bus electric vehicles, and off-road transportation electrification.

SCE's forecasts reflect a forecast that more closely aligns with expected decarbonization funding, mandates, and support policies. Policies such as states 5 million zero-emission vehicles goals on the roads in California by 2030 for light duty and CARB's Innovative Clean Transit and Advanced Clean Trucks rules for medium/heavy duty and buses were considered. SCE's previous forecast assumes the high electrification target levels that the state will have to achieve in meeting its aggressive long-term decarbonization goals and it is based on SCE's Clean Power and Electrification Pathway analysis. Compared to the previous forecast, SCE's updated EV forecast reflects a lower level of EV adoption due to the assumption changes. SCE projects that approximately 4.7 million light-duty EVs statewide (or 1.7 Million in SCE territory) are expected to be on the road by 2030.

Further post-model adjustments were made to incorporate impacts due to COVID-19, based on California vehicle auto sales post 2007-2009 recession, U.S. annual VMT post 2007-2009 recession for light duty EVs and external vendor outlooks on the effects of COVID-19 on the retail sales projections for non-light duty EVs.

Building Electrification

SCE forecasts future building electrification (BE) load growth for residential and commercial space and water heating. SCE's BE forecast more closely aligns with expected statewide decarbonization funding and support policies. Policies such as Building Energy Efficiency Standards - Title 24 and reach code were considered. SCE's previous forecast assumed the high electrification target levels that the state will have to achieve in meeting its aggressive long-term decarbonization goals and was is based on SCE's Clean Power and Electrification Pathway analysis. Compared to the previous forecast, SCE's updated BE forecast reflects a lower level of BE adoption due to the assumption changes.

Further post-model adjustments were made to incorporate impacts due to COVID-19, based on external vendor outlooks on the effects of COVID-19 on the housing starts and GDP.

Electricity Conservation Programs

SCE does not use energy efficiency (EE) as an explanatory variable in its econometric estimations. EE is assumed to be embedded in historical retail sales data and is deducted from the forecast of retail sales.

Over the past few months, the COVID-19 virus has impacted the ability of SCE EE Programs to capture EE savings. Customer touch programs (ESA and Direct Install) have been suspended, and other programs have been significantly changed (HERS). SCE updated the CEC AAEE forecast to reflect the COVID-19 impact. EE and Title 20 (T-20) codes and standards savings were adjusted using estimates of energy reduction and Title 24 (T-24) savings were adjusted using Moody's Analytics housing start forecast.

Other EX Post Modifications to the Sales Forecast

SCE makes some additional adjustments to the customer class sales forecast produced by the econometric models. The primary reason for this is that these components are all relatively new phenomena and thus cannot be explicitly modeled in the econometric equations. These components include transportation electrification, PV, building electrification, EE, battery storage, and climate change.

3) Historic Forecast Performance

SCE examines model statistics as one aspect of assessing forecast reasonableness. If the model statistics suggest a well specified model and estimated parameters conform to economic theory, we place some degree of confidence that the model will produce a reasonable forecast. For example, we generally accept a statistical relationship between electricity use and a variable thought to influence it only if the estimated parameter is at least twice the magnitude of its standard error. Also, we compare elasticities derived from the model and compare these to elasticities published in various studies or reported by other utilities.

We also perform in-sample simulations. That is, we test the models forecast performance over a period of time where simulated electricity use can be compared to actual electricity use.

Our forecasts are regularly and constantly evaluated with respect to accuracy. The basic evaluation is straightforward: the forecast prediction for a particular time period is compared to actual data, adjusted for weather variation as that data becomes available.

The basic metrics used in the evaluation are the Root Mean Squared Error (RMSE) and the Mean Absolute Percent Error (MAPE).

The definitions of RMSE and MAPE are as follows:

Suppose the forecast sample is j = T + 1, T + 2, …,T + *h*

Let $S_{F,t}$ represent predicted sales in period t and $S_{N,t}$ represent actual adjusted sales in period t; then:

RMSE = SQRT($\sum_{t=T+1} (S_{F,t} - S_{N,t})^2 / h$)

MAPE = 100 ● $\sum_{t=T+1} ABS((S_{F,t} - S_{N,t})/ S_{N,t}) / h$

The validation process with respect to the long-term sales forecast is undertaken monthly as each successive month's actual billed sales becomes available. As part of the validation process, the new month's billed sales are converted into weather and billing day adjusted values in order to eliminate variation in weather and billing days from the evaluation calculations.

An analysis of the 2019Q4 sales forecast compared to actual weather adjusted monthly sales for the period January 2020 to December 2020 reveals the following:

SCE Sales Forecast Evaluation for 2020

Month	Actual (Weather Adj.) MWh	Forecast Winter 2018Q4 Vintage MWh	MAPE Calculation
Jan-20	6,806,133	6,521,191	0.0428
Feb-20	5,618,912	5,889,036	0.0469
Mar-20	6,459,053	6,024,670	0.0696
Apr-20	5,669,494	5,989,816	0.0549
May-20	5,818,538	6,498,895	0.1105
Jun-20	6,759,980	6,836,170	0.0112
Jul-20	8,221,856	8,250,433	0.0035
Aug-20	7,999,425	8,378,689	0.0463
Sep-20	7,777,599	7,600,406	0.0230
Oct-20	7,624,926	6,906,400	0.0989
Nov-20	5,915,590	6,154,501	0.0396
Dec-20	7,034,454	6,658,696	0.0549

Jan-Dec Total (GWh)	81,706	81,709	
Simple Error - Jan-Dec	0.4%		
MAPE Error: Jan-Dec	5.0%		

The analysis shows that SCE's recent sales forecast in general tracks actual weather-adjusted retail sales closely for much of the year. The average simple error in 2209 is 0.4%.

4) Weather Adjustment Procedures

SCE has developed the weather and billing cycle adjustment model for the purpose of comparing recorded and weather adjusted sales on a monthly basis. Weather and the calendar have the most significant impact on the monthly and annual variations in electricity sales. The Weather Modeling System (WMS) is a SAS based program that calculates heating- and cooling-degree days (HDD/CDD) that correspond to the monthly billing cycle schedule rather than a calendar month.

The annual billing cycle consists of 12 schedules of 21-meter reading days distributed across the year. A monthly billing cycle consists of 21-meter read days. The 12 monthly billing cycles while approximating a calendar month are not required to be coincident with the calendar month. In addition, the number of days for between each meter read varies depending on the days in the month and the number of weekend days and holidays. The MWS, using daily temperatures and the number of days between each meter read, calculates the number of HDD/CDD for the 252 (12 x 21) meter read days in a year.

The electricity sales for each monthly billing cycle are disaggregated into each meter read. The electricity sales for the meter reads are statistically adjusted as a function of the difference between actual HDD/CDD for recorded number of days in the meter read. The adjusted electricity sales are then aggregated back into a monthly billing cycle.

The HDD/CDD is also adjusted for the changing distribution of customers within the service area. The WMS calculates customer-weighted average HDD/CDD using daily temperatures for the ten weather stations listed above. A further refinement is that the HDD/CDD are also adjusted according to the changing saturation of space conditioning appliances. Finally, separate sets of HDD/CDD are calculated for residential and non-residential electricity sales. A corresponding set of normal HDD/CCD, based on thirty years of history (1981 to 2010) are also calculated in the same manner.

The weather and billing day adjustment process is as follows:

Let $Y_{A,t}$ = actual billed sales per customer and $Y_{N,t}$ = adjusted sales per customer

Then $Y_{At} = \beta_0 + \beta_1 \bullet CDD_{A,t} + \beta_2 \bullet BDays_{A,t}$ and

$Y_{Nt} = \beta_0 + \beta_1 \bullet CDD_{N,t} + \beta_2 \bullet BDays_{N,t}$

Where $CDD_{A,t}$ is actual measured cooling degree days in the current time period, $BDays_{A,t}$ is actual measured billing days in the current time period, $CDD_{N,t}$ is normal cooling degree days and $BDays_{N,t}$ is normal billing days; β_1 and β_2 are coefficients that measure the relationship between a change in CDD and BDays respectively and a change in sales per customer.

The weather adjustment is:

$W_t = (Y_{A,t} - Y_{N,t}) \bullet Cust_t$ and Weather Adjusted sales are: $S_{N,t} = S_{A,t} - W_t$

5) Forecast Uncertainty

Suppose the "true" regression model is given by:

$$Y_t = x_t' ß + e_t$$

where e_t is an independent, and identically distributed, mean zero random disturbance, and ß is a vector of unknown parameters. The true model generating Y is not known, but we obtain estimates b of the unknown parameters. Then, setting the error term equal to its mean value of zero, the (point) forecasts of Y are obtained as:

$$y_t = x_t' b$$

Forecasts are made with error, where the error is simply the difference between the actual and forecasted value:

$$e_t = y_t - x_t' b$$

Assuming that the model is correctly specified, there are two sources of forecast error: residual uncertainty and coefficient uncertainty.

Residual Uncertainty

The first source of error, termed residual or innovation uncertainty, arises because the innovations e in the equation are unknown for the forecast period and are replaced with their expectations. While the residuals are zero in expected value, the individual values are non-zero; the larger the variation in the individual errors, the greater the overall error in the forecasts.

The standard measure of this variation is the standard error of the regression. Residual uncertainty is usually the largest source of forecast error.

Coefficient Uncertainty

The second source of forecast error is coefficient uncertainty. The estimated coefficients b of the equation deviates from the true coefficients ß in a random fashion. The standard error of the estimated coefficient, given in the regression output, is a measure of the precision with which the estimated coefficients measure the true coefficients.

The effect of coefficient uncertainty depends upon the exogenous variables. Since the estimated coefficients are multiplied by the exogenous variables in the computation of forecasts, the more the exogenous variables deviate from their mean values, the greater is the forecast uncertainty.

Forecast Variability

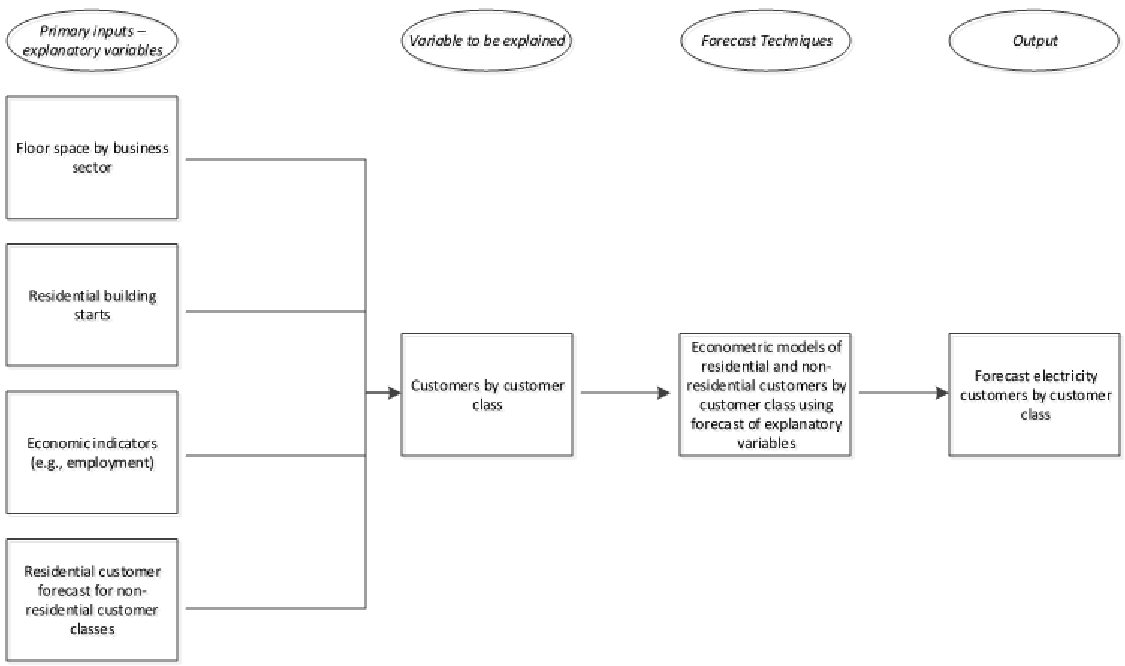
The variability of forecasts is measured by the forecast standard errors. For a single equation without lagged dependent variables or ARMA terms, the forecast standard errors are computed as:

$$se = s \sqrt{1 + x_t' (X'X)^{-1} x_t}$$

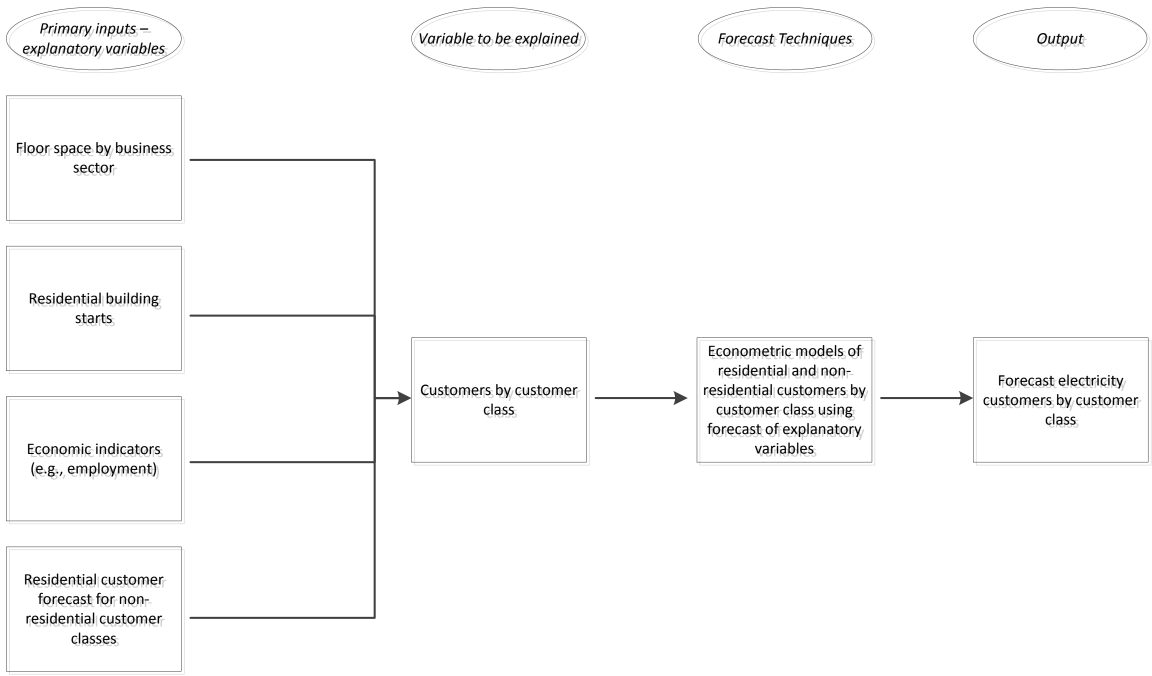
where s is the standard error of regression. These standard errors account for both innovation uncertainty (the first term) and coefficient uncertainty (the second term). Point forecasts made from linear regression models estimated by least squares are optimal in the sense that they have the smallest forecast variance among forecasts made by linear unbiased estimators. Moreover, if the innovations are normally distributed, the forecast errors have a t-distribution and forecast intervals can be readily formed. A two standard error band provides an approximate 95% forecast interval. In other words, if you (hypothetically) make many forecasts, the actual value of the dependent variable will fall inside these bounds 95 percent of the time. SCE constructs 95% confidence bands around its base case forecast based on the uncertainties described above.

6) Flow Diagram for Electric Use and Customer Modeling and Forecasting

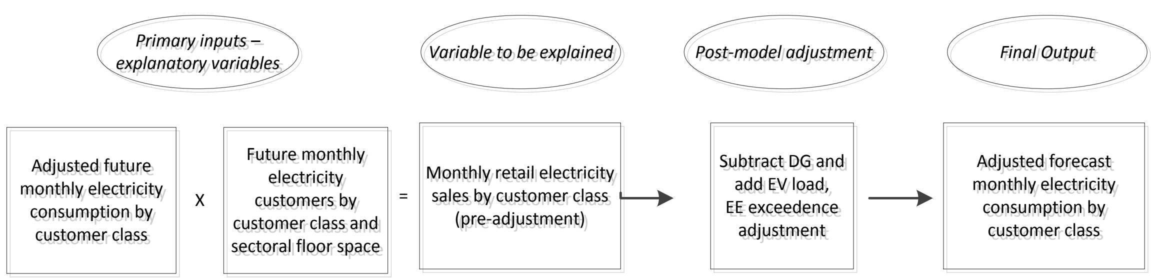
Electricity Consumption (kWh per Customer) Modeling and Forecasting



Electric Customer Modeling and Forecasting



Electric Retail Sales Modeling and Forecasting



7) Model Statistics – Electricity Use Models

The statistical details of the electricity consumption models are shown below. A glossary of variable names follows in Section 8.

Residential Electricity Use Model – L.A. County

Dependent Variable: LAUSE
Method: Least Squares
Sample: 2002M01 2020M08
Included observations: 224

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-1.1568	0.2630	-4.3987	0.0000
RES_LACDD*SUMSEAS*LASIZE	0.0000	0.0000	16.2579	0.0000
RES_LAHDD*WINSEAS*LASIZE	0.0000	0.0000	6.3456	0.0000
CUMBDAYS	0.0006	0.0001	7.8556	0.0000
LOG(LAGDP(-24))	0.2345	0.0502	4.6682	0.0000
RESRATE(-6)	-0.1375	0.2316	-0.5937	0.5534
RESCAC	-0.2721	0.0689	-3.9457	0.0001
JAN	0.0042	0.0085	0.4972	0.6196
FEB	-0.0331	0.0112	-2.9481	0.0036
MAR	-0.0287	0.0077	-3.7074	0.0003
APR	-0.0258	0.0096	-2.6791	0.0080
MAY	-0.0141	0.0129	-1.0928	0.2758
JUN	-0.0036	0.0129	-0.2822	0.7781
JUL	0.0124	0.0155	0.7957	0.4271
AUG	0.0309	0.0169	1.8248	0.0695
SEP	-0.0017	0.0175		0.9242
OCT	-0.0010	0.0140		0.9432
NOV	-0.0147	0.0109		0.1779
DUMMY_201808	0.1204	0.0252		0.0000
DUMMY_202007	0.1167	0.0246		0.0000

R-squared	0.9353	Mean dependent var	0.5246
Adjusted R-squared	0.9293	S.D. dependent var	0.0881
S.E. of regression	0.0234	Akaike info criterion	-4.5842
Sum squared resid	0.1120	Schwarz criterion	-4.2795
Log likelihood	533.4258	Hannan-Quinn criter.	-4.4612
F-statistic	155.1861	Durbin-Watson stat	1.7275
Prob(F-statistic)	0.0000		

LOG(LAGDP_COVID (-24)) indicates the log of Los Angeles County GDP lagged 24 periods.
Last sample observation is August 2020, first forecast period is September 2020

Residential Electricity Use Model – Orange County

Dependent Variable: ORUSE
Method: Least Squares
Sample: 2002M01 2020M08
Included observations: 224

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-0.5346	0.1643	-3.2541	0.0013
RES_ORCDD*SUMSEAS*ORSIZE	0.0000	0.0000	13.6595	0.0000
RES_ORHDD*WINSEAS*ORSIZE	0.0000	0.0000	4.2566	0.0000
CUMBDAYS	0.0008	0.0001	8.3588	0.0000
LOG(ORGDP(-24))	0.1823	0.0394	4.6244	0.0000
RESRATE(-6)	-0.2688	0.2754	-0.9758	0.3303
RESCAC	-0.3968	0.0688	-5.7662	0.0000
JAN	-0.0003	0.0102	-0.0343	0.9727
FEB	-0.0379	0.0134	-2.8247	0.0052
MAR	-0.0416	0.0091	-4.5606	0.0000
APR	-0.0363	0.0107	-3.4024	0.0008
MAY	-0.0275	0.0131	-2.1017	0.0368
JUN	-0.0128	0.0126	-1.0136	0.3120
JUL	0.0322	0.0135	2.3851	0.0180
AUG	0.0642	0.0146	4.3949	0.0000
SEP	0.0302	0.0158		0.0581
OCT	0.0080	0.0140		0.5672
NOV	-0.0210	0.0122		0.0874
DUMMY_201808	0.1284	0.0298		0.0000
DUMMY_202007	0.1027	0.0287		0.0004

R-squared	0.8992	Mean dependent var	0.5557
Adjusted R-squared	0.8898	S.D. dependent var	0.0832
S.E. of regression	0.0276	Akaike info criterion	-4.2553
Sum squared resid	0.1557	Schwarz criterion	-3.9507
Log likelihood	496.5951	Hannan-Quinn criter.	-4.1324
F-statistic	95.7566	Durbin-Watson stat	1.5568
Prob(F-statistic)	0.0000		

LOG(ORGDP_COVID (-24)) indicates the log of Orange County GDP lagged 24 periods.
Last sample observation is August 2020, first forecast period is September 2020

Residential Electricity Use Model – Riverside County

Dependent Variable: RVUSE
Method: Least Squares
Sample: 2008M01 2020M08
Included observations: 152

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	0.2093	0.3685	0.5679	0.5711
RES_RVCDD*SUMSEAS*RVSIZE	0.0000	0.0000	14.7783	0.0000
RES_RVHDD*WINSEAS*RVSIZE	0.0000	0.0000	2.9128	0.0042
CUMBDAYS	0.0007	0.0002	3.9841	0.0001
LOG(RVGDP(-6))	0.1044	0.0659	1.5837	0.1157
RESRATE(-9)	-3.1822	1.0895	-2.9207	0.0041
RESCAC	0.0045	0.1270	0.0351	0.9720
JAN	0.0131	0.0163	0.8069	0.4212
FEB	-0.0454	0.0225	-2.0197	0.0455
MAR	-0.0235	0.0146	-1.6060	0.1107
APR	0.0092	0.0194	0.4730	0.6370
MAY	-0.0418	0.0237	-1.7633	0.0802
JUN	-0.0458	0.0266	-1.7244	0.0870
JUL	0.0026	0.0398	0.0663	0.9472
AUG	0.0496	0.0443	1.1190	0.2652
SEP	-0.0324	0.0445		0.4687
OCT	-0.0326	0.0299		0.2769
NOV	0.0113	0.0205		0.5822
DUMMY_201508	-0.1419	0.0378		0.0003
DUMMY_201808	0.1192	0.0404		0.0037
DUMMY_202006	0.0770	0.0387		0.0486

R-squared	0.9796	Mean dependent var	0.7797
Adjusted R-squared	0.9765	S.D. dependent var	0.2352
S.E. of regression	0.0360	Akaike info criterion	-3.6811
Sum squared resid	0.1701	Schwarz criterion	-3.2633
Log likelihood	300.7617	Hannan-Quinn criter.	-3.5114
F-statistic	315.0091	Durbin-Watson stat	2.2917
Prob(F-statistic)	0.0000		

LOG (RVGDP_COVID (-9)) indicates the log of Riverside County GDP lagged 9 periods.
Last sample observation is August 2020, first forecast period is September 2020

Residential Electricity Use Model – San Bernardino County

Dependent Variable: SBUSE
Method: Least Squares
Sample: 2006M01 2020M08
Included observations: 176

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-0.2498	0.1782	-1.4023	0.1628
RES_SBCDD*SUMSEAS*SBSIZE	0.0000	0.0000	16.1909	0.0000
RES_SBHDD*WINSEAS*SBSIZE	0.0000	0.0000	4.5366	0.0000
CUMBDAYS	0.0007	0.0001	5.8482	0.0000
LOG(SBGDP(-9))	0.1186	0.0355	3.3432	0.0010
RESRATE(-9)	-0.8080	0.3894	-2.0751	0.0396
RESCAC	-0.0939	0.0528	-1.7784	0.0773
JAN	-0.0018	0.0118	-0.1494	0.8814
FEB	-0.0464	0.0160	-2.9049	0.0042
MAR	-0.0386	0.0108	-3.5712	0.0005
APR	-0.0204	0.0142	-1.4327	0.1540
MAY	-0.0186	0.0184	-1.0093	0.3144
JUN	0.0008	0.0193	0.0420	0.9666
JUL	0.0365	0.0271	1.3467	0.1801
AUG	0.0731	0.0292	2.5091	0.0131
SEP	0.0186	0.0293		0.5269
OCT	0.0082	0.0209		0.6946
NOV	-0.0107	0.0155		0.4923
DUMMY_201808	0.1168	0.0317		0.0003
DUMMY_202007	0.1490	0.0305		0.0000
DUMMY_202008	0.0680	0.0304		0.0268

R-squared	0.9757	Mean dependent var	0.6424
Adjusted R-squared	0.9725	S.D. dependent var	0.1733
S.E. of regression	0.0287	Akaike info criterion	-4.1509
Sum squared resid	0.1278	Schwarz criterion	-3.7726
Log likelihood	386.2772	Hannan-Quinn criter.	-3.9974
F-statistic	310.9634	Durbin-Watson stat	2.3183
Prob(F-statistic)	0.0000		

LOG (SBGDP_COVID (-9)) indicates the log of San Bernardino County GDP lagged 9 periods.
Last sample observation is August 2020, first forecast period is September 2020

Residential Electricity Use Model – Ventura/Santa Barbara Counties

Dependent Variable: VSBUSE
Method: Least Squares
Sample (adjusted): 2002M04 2020M08
Included observations: 221 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-0.4970	0.1389	-3.5780	0.0004
RES_VSBCDD*SUMSEAS*VSBSIZE	0.0000	0.0000	12.0600	0.0000
RES_VSBHDD*WINSEAS*VSBSIZE	0.0000	0.0000	6.8187	0.0000
CUMBDAYS	0.0007	0.0001	8.6763	0.0000
LOG(VSBGDP(-24))	0.2527	0.0445	5.6773	0.0000
RESRATE(-15)	-0.4287	0.2274	-1.8848	0.0609
RESCAC	-0.4037	0.0644	-6.2712	0.0000
JAN	0.0045	0.0080	0.5624	0.5745
FEB	-0.0416	0.0106	-3.9314	0.0001
MAR	-0.0338	0.0074	-4.5648	0.0000
APR	-0.0364	0.0086	-4.2253	0.0000
MAY	-0.0238	0.0115	-2.0719	0.0396
JUN	-0.0175	0.0113	-1.5486	0.1231
JUL	-0.0115	0.0130	-0.8812	0.3793
AUG	0.0011	0.0141	0.0773	0.9385
SEP	-0.0259	0.0149		0.0846
OCT	-0.0141	0.0125		0.2602
NOV	-0.0234	0.0099		0.0189
DUMMY_200812	0.0151	0.0231		0.5149
DUMMY_201411	-0.0627	0.0227		0.0063
DUMMY_201601	-0.0546	0.0229		0.0179
DUMMY_201808	0.1198	0.0233	5.1398	0.0000
DUMMY_202007	0.1003	0.0229	4.3795	0.0000

R-squared	0.8863	Mean dependent var	0.5565
Adjusted R-squared	0.8737	S.D. dependent var	0.0616
S.E. of regression	0.0219	Akaike info criterion	-4.7070
Sum squared resid	0.0949	Schwarz criterion	-4.3533
Log likelihood	543.1189	Hannan-Quinn criter.	-4.5642
F-statistic	70.1776	Durbin-Watson stat	1.6829

LOG (VSBGDP_COVID (-24)) indicates the log of Ventura/Santa Barbara County GDP lagged 24 periods.
Last sample observation is August 2020, first forecast period is September 2020

Residential Electricity Use Model – Other (Rural) Counties

Dependent Variable: OTHUSE
Method: Least Squares
Sample: 2004M01 2020M08
Included observations: 200

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-0.2843	0.1250	-2.2748	0.0241
RES_OTHCDD*SUMSEAS*OTHSIZE	0.0000	0.0000	14.8528	0.0000
RES_OTHHDD*WINSEAS*OTHSIZE	0.0000	0.0000	5.1034	0.0000
CUMBDAYS	0.0007	0.0001	6.2074	0.0000
LOG(OTHGDP(-3))	0.1661	0.0406	4.0920	0.0001
RESRATE	-0.6694	0.3010	-2.2240	0.0274
RESCAC	-0.1132	0.0578	-1.9580	0.0518
JAN	0.0157	0.0123	1.2745	0.2041
FEB	-0.0226	0.0156	-1.4515	0.1484
MAR	-0.0056	0.0126	-0.4425	0.6586
APR	0.0089	0.0183	0.4860	0.6276
MAY	0.0349	0.0265	1.3196	0.1887
JUN	0.0627	0.0286	2.1948	0.0295
JUL	0.0890	0.0371	2.3962	0.0176
AUG	0.1159	0.0389	2.9806	0.0033
SEP	0.0567	0.0349		0.1057
OCT	0.0493	0.0274		0.0733
NOV	-0.0121	0.0190		0.5238
DUMMY_202007	0.2100	0.0320		0.0000
DUMMY_202008	0.0882	0.0321		0.0066

R-squared	0.9741	Mean dependent var	0.6677
Adjusted R-squared	0.9713	S.D. dependent var	0.1802
S.E. of regression	0.0305	Akaike info criterion	-4.0466
Sum squared resid	0.1676	Schwarz criterion	-3.7167
Log likelihood	424.6558	Hannan-Quinn criter.	-3.9131
F-statistic	355.8206	Durbin-Watson stat	1.9188
Prob(F-statistic)	0.0000		

LOG (OTHGDP_COVID (-3)) indicates the log of other/rurals Counties GDP lagged 3 periods.
Last sample observation is August 2020, first forecast period is September 2020

Commercial Electricity Use Model

Dependent Variable: COMUSE
Method: Least Squares
Sample: 2004M01 2020M08
Included observations: 200

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-14.5549	2.6404	-5.5124	0.0000
COM_CDD*SUMSEAS*COMSIZE	0.0000	0.0000	4.8183	0.0000
CUMBDAYS	0.0077	0.0009	8.7633	0.0000
LOG(SCEGDP(-3))	3.3179	0.4545	7.2996	0.0000
COMRATE	0.0003	0.0291	0.0091	0.9927
JAN	-0.3121	0.0826	-3.7782	0.0002
FEB	-0.0978	0.1204	-0.8116	0.4181
MAR	-0.0926	0.0825	-1.1224	0.2632
APR	0.1615	0.0977	1.6522	0.1002
MAY	0.1320	0.0943	1.3990	0.1635
JUN	0.3198	0.0918	3.4856	0.0006
JUL	0.4186	0.1330	3.1480	0.0019
AUG	0.7509	0.1555	4.8300	0.0000
SEP	0.3594	0.1595	2.2534	0.0254
OCT	0.5422	0.1118	4.8504	0.0000
NOV	0.1024	0.0966		0.2908
NONRESCAC	-7.5670	0.8644		0.0000
DUMMY_202004	-0.6228	0.2482		0.0130

R-squared	0.8749	Mean dependent var	6.4227
Adjusted R-squared	0.8632	S.D. dependent var	0.6393
S.E. of regression	0.2365	Akaike info criterion	0.0397
Sum squared resid	10.1772	Schwarz criterion	0.3366
Log likelihood	14.0286	Hannan-Quinn criter.	0.1598
F-statistic	74.8403	Durbin-Watson stat	2.5190
Prob(F-statistic)	0.0000		

LOG (SCEGDP_COVID (-3)) indicates the log of SCE GDP lagged 3 periods.
Last sample observation is August 2020, first forecast period is September 2020

Industrial Electricity Use Model

Dependent Variable: INDUSE
Method: Least Squares
Sample: 2008M01 2020M08
Included observations: 152

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	2.7692	0.4192	6.6055	0.0000
COM_CDD*SUMSEAS	0.0007	0.0004	1.8050	0.0733
INDRATE(-15)	-0.0613	0.0164	-3.7340	0.0003
CUMBDAYS	0.0017	0.0005	3.1356	0.0021
INDTREND	-0.0059	0.0003	-17.0053	0.0000
JAN	-0.0944	0.0478	-1.9761	0.0502
FEB	-0.0332	0.0729	-0.4558	0.6493
MAR	0.0149	0.0479	0.3119	0.7556
APR	0.0658	0.0593	1.1107	0.2687
MAY	0.1193	0.0577	2.0677	0.0406
JUN	0.1164	0.0547	2.1293	0.0351
JUL	0.0903	0.0786	1.1484	0.2529
AUG	0.2065	0.0934	2.2125	0.0286
SEP	-0.0006	0.0979	-0.0065	0.9948
OCT	0.0986	0.0690	1.4275	0.1558
NOV	0.0546	0.0587		0.3536
DUMMY_202005	-0.2274	0.1257		0.0727
DUMMY_202008	-0.2460	0.1255		0.0520

R-squared	0.8362	Mean dependent var	2.5409
Adjusted R-squared	0.8154	S.D. dependent var	0.2776
S.E. of regression	0.1193	Akaike info criterion	-1.3038
Sum squared resid	1.9066	Schwarz criterion	-0.9458
Log likelihood	117.0923	Hannan-Quinn criter.	-1.1584
F-statistic	40.2309	Durbin-Watson stat	1.0203
Prob(F-statistic)	0.0000		

INDRATE(-15) indicates the log of SCE industrial rates lagged 15 months.
Last sample observation is August 2020, first forecast period is September 2020

Other Public Authority Electricity Use Model

Dependent Variable: OPAUSE
Method: Least Squares
Sample: 2008M01 2020M08
Included observations: 152

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-1.7266	2.1355	-0.8085	0.4202
COM_CDD	0.0005	0.0002	2.5103	0.0133
NONRESCAC	-7.9188	1.0071	-7.8632	0.0000
OPARATE(-12)	-0.0279	0.0094	-2.9627	0.0036
LOG(SCEGOVEMP(-9))	1.3724	0.2222	6.1764	0.0000
CUMBDAYS	0.0014	0.0003	4.5582	0.0000
LIGHTINDEX	0.7654	0.1764	4.3397	0.0000
JAN	-0.1205	0.0263	-4.5730	0.0000
FEB	-0.0802	0.0403	-1.9916	0.0484
MAR	-0.0278	0.0264	-1.0511	0.2951
APR	0.1215	0.0368	3.2991	0.0012
MAY	0.1758	0.0347	5.0733	0.0000
JUN	0.1680	0.0305	5.5147	0.0000
JUL	0.1204	0.0432	2.7837	0.0062
AUG	0.1801	0.0517	3.4828	0.0007
SEP	0.1877	0.0544		0.0007
OCT	0.2334	0.0376		0.0000
NOV	0.0301	0.0328		0.3606

R-squared	0.9109	Mean dependent var	1.3474
Adjusted R-squared	0.8996	S.D. dependent var	0.2074
S.E. of regression	0.0657	Akaike info criterion	-2.4959
Sum squared resid	0.5789	Schwarz criterion	-2.1378
Log likelihood	207.6863	Hannan-Quinn criter.	-2.3504
F-statistic	80.5446	Durbin-Watson stat	2.1974
Prob(F-statistic)	0.0000		

OPARATE(-12) indicates the log of SCE OPA rates lagged 12 months.
LOG(SCEGOVEMP_COVID(-9)) indicates a log of SCE government employment lagged 9 months
Last sample observation is August 2020, first forecast period is September 2020

Agriculture Electricity Use Model

Dependent Variable: AGUSE
Method: Least Squares
Sample: 2008M01 2020M08
Included observations: 152

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-38.6911	4.9689	-7.7867	0.0000
CUMBDAYS	0.0028	0.0033	0.8648	0.3887
LOG(SCEGDP(-3))	5.7724	0.6299	9.1635	0.0000
RUNOFF	-0.0032	0.0004	-7.6306	0.0000
JAN	-0.5974	0.2853	-2.0942	0.0381
FEB	-0.4576	0.4354	-1.0510	0.2952
MAR	0.6436	0.2886	2.2298	0.0274
APR	2.0603	0.3609	5.7089	0.0000
MAY	3.2393	0.3496	9.2661	0.0000
JUN	5.2470	0.3288	15.9586	0.0000
JUL	6.3705	0.3212	19.8318	0.0000
AUG	6.0035	0.3113	19.2836	0.0000
SEP	4.2604	0.3223	13.2202	0.0000
OCT	2.8670	0.3168	9.0500	0.0000
NOV	0.7576	0.3503	2.1630	0.0323
DUMMY_201705	4.3285	0.7551		0.0000
AGDUMMY2012_2017	1.0166	0.1189		0.0000
DUMMY_202004	-1.9515	0.7541		0.0107

R-squared	0.9304	Mean dependent var	6.2887
Adjusted R-squared	0.9216	S.D. dependent var	2.5420
S.E. of regression	0.7117	Akaike info criterion	2.2686
Sum squared resid	67.8824	Schwarz criterion	2.6267
Log likelihood	-154.4148	Hannan-Quinn criter.	2.4141
F-statistic	105.4175	Durbin-Watson stat	1.3574
Prob(F-statistic)	0.0000		

LOG(SCEGDP_COVID(-3)) indicates a log of SCE GDP lagged 3 months
Last sample observation is August 2020, first forecast period is September 2020

Street Light Electricity Use Model

Dependent Variable: STLUSE
Method: Least Squares
Sample: 2008M01 2019M10
Included observations: 142

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-0.0768	0.3019	-0.2544	0.7996
CUMBDAYS	0.0010	0.0004	2.4417	0.0159
RESPRSTL	0.0112	0.0004	24.8554	0.0000
DAYHRS	-0.0005	0.0003	-1.8582	0.0653
LIGHTINDEX	-0.5401	0.0575	-9.3860	0.0000

R-squared	0.8428	Mean dependent var	2.8442
Adjusted R-squared	0.8382	S.D. dependent var	0.3831
S.E. of regression	0.1541	Akaike info criterion	-0.8683
Sum squared resid	3.2518	Schwarz criterion	-0.7642
Log likelihood	66.6501	Hannan-Quinn criter.	-0.8260
F-statistic	183.6732	Durbin-Watson stat	1.2980
Prob(F-statistic)	0.0000		

Last sample observation is August 2020, first forecast period is September 2020

8) Electricity Use Model Variable Description

Residential Electricity Use Model

ResUse	Recorded residential class monthly electricity consumption in kWh per customer. Source: SCE.
CDD	Cooling degree-days. Sources: SCE and National Weather Service
HDD	Heating degree-days. Sources: SCE and National Weather Service
ResRate	Residential constant $2009 dollar price of electricity in cents per kWh. Source: SCE and IHS Global Insight
RESCAC	An index measuring the average efficiency of residential air conditioning equipment. Compiled from Energy Information Administration data.
CUMBDAYS	Average number of days in monthly billing statement multiplied by the number of billing cycles in month. Source: SCE
GeoGDP	Regional output in 2012 dollars. Compiled from Moody's Analytics data.
JAN-DEC	Binary variable set equal to 1 for the designated month and zero otherwise.
GeoSIZE	Average residential household size in square feet. Compiled from Dodge Data & Analytics data.
SUMSEAS	A binary equal to 1 during the summer months April to October and zero otherwise.
WINSEAS	A binary equal to 1 during the winter months November to March and zero otherwise.
DUMMY_YYYYMMMM	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in customer data.
LA	Prefix in front of variable name to denote Los Angeles County.
OR	Prefix in front of variable name to denote Orange County.
SB	Prefix in front of variable name to denote San Bernardino County.
RIV	Prefix in front of variable name to denote Riverside County.
VEN	Prefix in front of variable name to denote Ventura and Santa Barbara Counties.
OTH	Prefix in front of variable name to denote Rural Counties (Fresno, Inyo, Kern Kings, Mono and Tulare)

Commercial Electricity Use Model

COMUSE	Recorded commercial class monthly electricity consumption in MWh per commercial customer. Source: SCE
COMCDD	Non-residential cooling degree-days, dynamic population share weighted. Sources: SCE and National Weather Service
SCEGDP	SCE regional output in 2012 dollars. Compiled from Moody's Analytics data.
COMSIZE	Average commercial building size in square feet. Sources: Dodge Data & Analytics and SCE
CUMBDAYS	Average number of days in monthly billing statement multiplied by the number of billing cycles in month. Source: SCE
JAN-NOV	Binary variable set equal to 1 for the designated month and zero otherwise
SUMSEAS	A binary equal to 1 during the summer months May to October and zero otherwise
NONRESCAC	An index measuring the average efficiency of commercial air conditioning equipment. Compiled from Energy Information Administration data.

Industrial Electricity Use Model

INDUSE	Recorded industrial class monthly electricity consumption in kWh per industrial building square feet. Sources: SCE and Dodge Data & Analytics
COMCDD	Non-residential cooling degree-days static population weighting. Sources: SCE and National Weather Service
INDRATE	Industrial class constant $2012 dollar price of electricity in cents per kWh. Sources: SCE and IHS Global Insight
SCEMFGEMP	SCE Manufacturing employment. Compiled from Moody's Analytics data.
CUMBDAYS	Average number of days in monthly billing statement multiplied by the number of billing cycles in a month. Source: SCE
JAN-NOV	Binary variable set equal to 1 for the designated month and zero otherwise
SUMSEAS	A binary equal to 1 during the summer months May to October and zero otherwise
IND_TREND	Linear counter variable designed to capture secular trend in industrial class electricity consumption not otherwise captured in the model

Other Public Authority Electricity Use Model

OPAUSE	Recorded other public authority class monthly electricity consumption in kWh per government building square feet. Sources: SCE and Dodge Data & Analytics
COMCDD	Non-residential cooling degree-days, static population weighted. Sources: SCE and National Weather Service
OPARATE	Other public authority class constant $2012 dollar price of electricity in cents per kWh. Sources: SCE and IHS Global Insight
SCEGOVEMP	Government employment. Compiled from Moody's Analytics data.
CUMBDAYS	Average number of days in monthly billing statement multiplied by the number of billing cycles in month. Source: SCE
LIGHTINDX	An index of commercial building lighting efficiency, Compiled from Energy Information Administration data.
JAN-NOV	Binary variable set equal to 1 for the designated month and zero otherwise.
NONRESCAC	An index measuring the average efficiency of commercial air conditioning equipment. Compiled from Energy Information Administration data.

Agriculture Electricity Use Model

AGRUSE	Recorded agriculture class monthly electricity consumption in MWh per agriculture customer. Source: SCE
CUMBDAYS	Average number of days in monthly billing statement multiplied by the number of billing cycles in month. Source: SCE
RUNOFF	Full natural flow of San Joaquin River at Friant Dam in cubic feet of flow per second. Sources: U.S Department of the Interior and SCE
JAN-NOV	Binary variable set equal to 1 for the designated month and zero otherwise.
AGRDUMMY2012_2017	Binary variables equal to one from 2012 to 2017 and zero otherwise, that are designed to drought-impacted usage data.

Street Light Electricity Use Model

STLUSE	Recorded street light class electricity monthly consumption in MWh per street light customer. Source: SCE
RESPRSTLT	Number of residential customers per street lighting customer. Source: SCE.
CUMBDAYS	Average number of days in monthly billing statement multiplied by the number of billing cycles in month. Source: SCE.
DAYHRS	Number of hours of daylight in a month in Southern California (a proxy for office lighting use). Source: SCE
LIGHTINDEX	An index of commercial building lighting efficiency. Compiled from Energy Information Administration data.

9) Model Statistics – Customer Models

The statistical details of the residential and non-residential customer models are shown below, while a glossary of terms follows at the end of Section 10. The residential customer models are constructed on the basis that new customers are determined mainly by housing starts (with a lag extending from zero up to 24 months depending upon the region). The housing start forecast is from Moody's Analytics.

Note that in the case of the industrial and other public authority (OPA) customer classes, the sales forecasts are constructed as the product of electricity consumption per square foot and total building square feet. Thus, the forecasts of Industrial class customers and OPA customer are independent of industrial and OPA customer class sales. An independent forecast of building square feet by building type is provided by Dodge Data & Analytics.

Residential Electricity Customer Model – L.A. County

Dependent Variable: D(LACUS)
Method: Least Squares
Sample: 2006M01 2020M08
Included observations: 176

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-171.5431	178.1845	-0.9627	0.3372
LASTRT_ADJ	0.0392	0.0188	2.0833	0.0388
JAN	550.3856	205.7981	2.6744	0.0083
FEB	583.1043	205.8085	2.8332	0.0052
MAR	411.7730	209.1560	1.9687	0.0507
APR	394.8200	209.1661	1.8876	0.0609
MAY	247.4687	205.6406	1.2034	0.2306
JUN	142.7337	205.6713	0.6940	0.4887
JUL	253.5194	213.2452	1.1889	0.2363
AUG	167.4321	209.4293	0.7995	0.4252
SEP	400.5825	209.1971	1.9149	0.0573
OCT	411.8508	209.1656	1.9690	0.0507
NOV	302.4962	213.1423	1.4192	0.1578
DUMMY_201707	-4,574.7980	575.2103	-7.9533	0.0000
DUMMY_201708	4,623.3490	574.5340	8.0471	0.0000
DUMMY_201803	-3,221.8160	581.5182		0.0000
DUMMY_201804	3,244.4770	579.6779		0.0000
DUMMY_201811	1,781.2560	574.4855		0.0023
DUMMY_202007	2,433.6860	574.8433		0.0000

R-squared	0.6154	Mean dependent var	383.6534
Adjusted R-squared	0.5713	S.D. dependent var	845.1748
S.E. of regression	553.3743	Akaike info criterion	15.5716
Sum squared resid	48,077,035.0000	Schwarz criterion	15.9139
Log likelihood	-1,351.3020	Hannan-Quinn criter.	15.7104
F-statistic	13.9566	Durbin-Watson stat	2.5379
Prob(F-statistic)	0.0000		

Last sample observation is August 2020, first forecast period is September 2020

Residential Electricity Customer Model – Orange County

Dependent Variable: D(ORCUS)
Method: Least Squares
Sample: 2008M01 2020M08
Included observations: 152

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	187.2630	118.6511	1.5783	0.1170
ORSTRT_ADJ(-3)	0.0364	0.0105	3.4786	0.0007
JAN	85.3744	141.3201	0.6041	0.5468
FEB	56.5184	141.3355	0.3999	0.6899
MAR	13.1567	144.1159	0.0913	0.9274
APR	36.2472	144.1194	0.2515	0.8018
MAY	67.9659	144.1180	0.4716	0.6380
JUN	-92.6056	147.3550	-0.6285	0.5308
JUL	178.2501	147.3578	1.2096	0.2286
AUG	29.5553	147.3551	0.2006	0.8413
SEP	-1.8647	147.3741	-0.0127	0.9899
OCT	218.6635	144.1165	1.5173	0.1316
NOV	254.6958	144.1244	1.7672	0.0796
DUMMY_201705	-1,208.3940	367.7781	-3.2857	0.0013
DUMMY_201706	1,181.2150	369.0458	3.2007	0.0017
DUMMY_201707	-3,615.8170	369.3649	-9.7893	0.0000
DUMMY_201708	3,624.6170	369.7391	9.8032	0.0000
DUMMY_201803	-1,582.8680	369.2734	-4.2864	0.0000
DUMMY_201804	2,053.4180	369.9187	5.5510	0.0000
DUMMY_201908	-932.1130	368.7117	-2.5280	0.0127
DUMMY_201909	903.9839	368.8531	2.4508	0.0156
DUMMY_202006	-945.1357	368.8718	-2.5622	0.0115
DUMMY_202007	1,311.4180	368.7382	3.5565	0.0005

R-squared	0.7242	Mean dependent var	477.9013
Adjusted R-squared	0.6772	S.D. dependent var	621.3164
S.E. of regression	353.0104	Akaike info criterion	14.7094
Sum squared resid	16,075,506.0000	Schwarz criterion	15.1670
Log likelihood	-1,094.9170	Hannan-Quinn criter.	14.8953
F-statistic	15.3984	Durbin-Watson stat	2.2707
Prob(F-statistic)	0.0000		

Last sample observation is August 2020, first forecast period is September 2020
ORSTRT_COVID(-3) indicates Orange County's total housing starts lagging 3 months

Residential Electricity Customer Model – Riverside County

Dependent Variable: D(RVCUS)
Method: Least Squares
Sample: 2008M01 2020M08
Included observations: 152

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	184.3880	100.0378	1.8432	0.0676
RVSTRT_ADJ	0.0475	0.0166	2.8514	0.0051
JAN	67.1397	104.4997	0.6425	0.5217
FEB	127.9798	106.6264	1.2003	0.2323
MAR	84.4990	106.6059	0.7926	0.4295
APR	39.1679	106.6242	0.3673	0.7140
MAY	68.7882	106.7097	0.6446	0.5203
JUN	92.6437	109.0451	0.8496	0.3971
JUL	193.6279	111.8498	1.7311	0.0858
AUG	10.0490	109.2102	0.0920	0.9268
SEP	86.1481	106.5911	0.8082	0.4205
OCT	116.2978	106.5785	1.0912	0.2772
NOV	231.7480	106.5721	2.1746	0.0315
DUMMY_201202	711.3364	274.0589	2.5956	0.0105
DUMMY_201206	-1,043.1380	273.6661	-3.8117	0.0002
DUMMY_201207	823.9813	274.8591		0.0033
DUMMY_201705	-1,699.4820	277.9653		0.0000
DUMMY_201706	1,201.0490	278.5289		0.0000
DUMMY_201707	-1,733.7770	278.1000		0.0000
DUMMY_201708	2,138.1210	275.5482		0.0000
DUMMY_201803	-1,779.0830	275.4213		0.0000
DUMMY_201804	1,464.1380	275.0220	5.3237	0.0000
DUMMY_201908	-1,548.8200	274.5758	-5.6408	0.0000
DUMMY_202007	646.1798	273.8166	2.3599	0.0198

R-squared	0.7237	Mean dependent var	457.1645
Adjusted R-squared	0.6741	S.D. dependent var	457.2211
S.E. of regression	261.0359	Akaike info criterion	14.1111
Sum squared resid	8,721,888.0000	Schwarz criterion	14.5886
Log likelihood	-1,048.4460	Hannan-Quinn criter.	14.3051
F-statistic	14.5767	Durbin-Watson stat	2.3593
Prob(F-statistic)	0.0000		

Last sample observation is August 2020, first forecast period is September 2020

Residential Electricity Customer Model – San Bernardino County

Dependent Variable: D(SBCUS)
Method: Least Squares
Sample: 2008M01 2020M08
Included observations: 152

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-22.5637	95.7082	-0.2358	0.8140
SBSTRT_ADJ	0.0507	0.0144	3.5219	0.0006
JAN	285.1674	109.5002	2.6043	0.0103
FEB	323.5334	109.5012	2.9546	0.0037
MAR	218.0527	111.7278	1.9516	0.0532
APR	386.3607	111.7431	3.4576	0.0007
MAY	186.9024	111.7876	1.6719	0.0970
JUN	132.6238	114.2355	1.1610	0.2478
JUL	144.8022	117.1617	1.2359	0.2188
AUG	120.0667	114.3589	1.0499	0.2957
SEP	111.6166	111.6822	0.9994	0.3195
OCT	216.2380	111.6760	1.9363	0.0550
NOV	86.0231	114.1972	0.7533	0.4527
DUMMY_201206	-1,208.0600	286.5903	-4.2153	0.0000
DUMMY_201207	1,102.9540	287.8381	3.8319	0.0002
DUMMY_201705	-1,783.7360	290.3125		0.0000
DUMMY_201706	947.0755	291.1789		0.0015
DUMMY_201707	-1,128.7240	290.9203		0.0002
DUMMY_201708	1,276.1250	288.7069		0.0000
DUMMY_201803	-1,194.1860	289.1031		0.0001
DUMMY_201804	1,276.0600	288.7644		0.0000
DUMMY_201908	-809.9808	287.2342	-2.8199	0.0056
DUMMY_201811	1,098.8690	286.1602	3.8400	0.0002
DUMMY_202007	1,052.9410	286.8921	3.6702	0.0004

R-squared	0.6556	Mean dependent var	356.4013
Adjusted R-squared	0.5937	S.D. dependent var	429.1112
S.E. of regression	273.5313	Akaike info criterion	14.2047
Sum squared resid	9,576,881.0000	Schwarz criterion	14.6821
Log likelihood	-1,055.5530	Hannan-Quinn criter.	14.3986
F-statistic	10.5923	Durbin-Watson stat	2.1779
Prob(F-statistic)	0.0000		

Last sample observation is August 2020, first forecast period is September 2020

Residential Electricity Customer Model – Ventura/Santa Barbara Counties

Dependent Variable: D(VSBCUS)
Method: Least Squares
Sample: 2008M01 2020M08
Included observations: 152

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-6.8464	50.9986	-0.1342	0.8934
VSBSTRT_ADJ(-12)	0.0422	0.0199	2.1230	0.0357
JAN	93.4427	62.7560	1.4890	0.1389
FEB	66.8394	62.7609	1.0650	0.2889
MAR	39.7676	65.2923	0.6091	0.5435
APR	54.3168	63.9111	0.8499	0.3970
MAY	30.7546	62.7799	0.4899	0.6250
JUN	-134.0522	63.9241	-2.0971	0.0379
JUL	164.4653	65.2902	2.5190	0.0130
AUG	71.5002	65.2814	1.0953	0.2754
SEP	197.0675	63.9127	3.0834	0.0025
OCT	105.1126	63.9190	1.6445	0.1025
NOV	127.8571	63.9242	2.0001	0.0476
DUMMY_201503	529.4068	159.9054	3.3108	0.0012
DUMMY_201707	-1,336.0260	159.9110	-8.3548	0.0000
DUMMY_201708	1,159.9890	159.9361		0.0000
DUMMY_201712	-566.8514	160.8861		0.0006
DUMMY_201803	-887.7624	160.7149		0.0000
DUMMY_201804	994.2240	161.4113		0.0000
DUMMY_201908	-1,079.9120	160.0742		0.0000
DUMMY_202006	-268.5168	159.5785		0.0948
DUMMY_202007	523.2066	159.9855	3.2703	0.0014

R-squared	0.7272	Mean dependent var	104.1053
Adjusted R-squared	0.6832	S.D. dependent var	271.9821
S.E. of regression	153.0970	Akaike info criterion	13.0332
Sum squared resid	3,047,032.0000	Schwarz criterion	13.4708
Log likelihood	-968.5193	Hannan-Quinn criter.	13.2109
F-statistic	16.5032	Durbin-Watson stat	2.4328
Prob(F-statistic)	0.0000		

VBSTRT_ADJ(-12) indicates Ventura/Santa Barbara County's total housing starts lagging 12 months
Last sample observation is August 2020, first forecast period is September 2020

Residential Electricity Customer Model – Other (Rural) Counties

Dependent Variable: D(OTHCUS)
Method: Least Squares
Sample: 2008M01 2020M08
Included observations: 152

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-3.3021	39.8968	-0.0828	0.9342
OTHSTRT_ADJ(-6)	0.0742	0.0199	3.7249	0.0003
JAN	59.3983	40.9651	1.4500	0.1495
FEB	26.9573	40.9432	0.6584	0.5115
MAR	24.1188	41.7490	0.5777	0.5645
APR	48.7789	42.6903	1.1426	0.2553
MAY	58.8580	41.7489	1.4098	0.1610
JUN	33.8399	41.7497	0.8105	0.4191
JUL	-24.2338	42.6980	-0.5676	0.5713
AUG	15.7266	42.6944	0.3684	0.7132
SEP	59.0740	42.6873	1.3839	0.1688
OCT	-18.0176	41.7549	-0.4315	0.6668
NOV	30.3868	41.7525	0.7278	0.4681
DUMMY_201704	347.4030	107.1801	3.2413	0.0015
DUMMY_201705	-557.9091	106.8743	-5.2202	0.0000
DUMMY_201706	342.2941	106.8555		0.0017
DUMMY_201707	-375.4749	107.1478		0.0006
DUMMY_201708	412.0795	106.9527		0.0002
DUMMY_201709	-271.5611	106.8881		0.0123
DUMMY_201803	-719.0577	106.4536		0.0000
DUMMY_201804	818.3893	106.8385		0.0000
DUMMY_201908	-433.9549	106.8173	-4.0626	0.0001
DUMMY_202007	354.2278	108.7391	3.2576	0.0014

R-squared	0.6714	Mean dependent var	125.3289
Adjusted R-squared	0.6153	S.D. dependent var	164.8865
S.E. of regression	102.2630	Akaike info criterion	12.2315
Sum squared resid	1,349,045.0000	Schwarz criterion	12.6891
Log likelihood	-906.5967	Hannan-Quinn criter.	12.4174
F-statistic	11.9802	Durbin-Watson stat	2.2881
Prob(F-statistic)	0.0000		

Last sample observation is August 2020, first forecast period is September 2020
OTHSTRT_ADJ(-6) indicates Other/Rurals Counties' total housing starts lagging 6 months

Commercial Customer Model

Dependent Variable: D(COMCUS)
Method: Least Squares
Sample: 2004M01 2020M08
Included observations: 200

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	115.3245	88.1267	1.3086	0.1923
D(SCERESCUSF)	0.1300	0.0118	11.0029	0.0000
JAN	-80.9820	121.6091	-0.6659	0.5063
FEB	42.8833	120.0873	0.3571	0.7214
MAR	135.4854	121.2544	1.1174	0.2653
APR	-34.1923	122.4096	-0.2793	0.7803
MAY	102.6312	123.3618	0.8320	0.4065
JUN	282.7137	121.2102	2.3324	0.0208
JUL	-51.8075	122.1519	-0.4241	0.6720
AUG	63.5708	121.1716	0.5246	0.6005
SEP	-37.6792	121.7597	-0.3095	0.7573
OCT	60.8729	121.6308	0.5005	0.6174
NOV	-28.8181	121.7250	-0.2367	0.8131
DUMMY_201701	-2,046.7910	354.2641	-5.7776	0.0000
DUMMY_201705	-4,618.2060	365.1778	-12.6465	0.0000
DUMMY_201706	3,076.0580	359.5019	8.5564	0.0000
DUMMY_201707	1,741.9280	386.8500	4.5029	0.0000
DUMMY_201708	1,821.1200	386.7048	4.7093	0.0000
DUMMY_201903	-5,431.8330	353.2599	-15.3763	0.0000
DUMMY_201904	3,561.1480	353.5343	10.0730	0.0000
DUMMY_201905	1,495.3700	354.0546	4.2236	0.0000

R-squared	0.8512	Mean dependent var	470.8950
Adjusted R-squared	0.8345	S.D. dependent var	842.5288
S.E. of regression	342.7066	Akaike info criterion	14.6107
Sum squared resid	21,023,157.0000	Schwarz criterion	14.9570
Log likelihood	-1,440.0690	Hannan-Quinn criter.	14.7509
F-statistic	51.1878	Durbin-Watson stat	1.2001
Prob(F-statistic)	0.0000		

The D_ indicates the first difference
Last sample observation is August 2020, first forecast period is September 2020

Industrial Customer Model

Dependent Variable: D(INDCUS)
Method: Least Squares
Sample: 2006M01 2020M08
Included observations: 176

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-68.1862	11.6637	-5.8460	0.0000
D(SCEMFGEMP(-3))	3.7462	0.6690	5.5998	0.0000
INDTREND	0.2433	0.0527	4.6155	0.0000
JAN	-2.6545	12.7134	-0.2088	0.8349
FEB	-5.9007	12.4963	-0.4722	0.6375
MAR	6.7803	13.0002	0.5216	0.6027
APR	27.9065	13.1559	2.1212	0.0355
MAY	-0.3918	12.8558	-0.0305	0.9757
JUN	14.1187	12.6953	1.1121	0.2679
JUL	11.6728	12.4955	0.9342	0.3517
AUG	9.9229	12.7457	0.7785	0.4375
SEP	3.5801	12.9220	0.2771	0.7821
OCT	14.3802	13.0808	1.0993	0.2734
NOV	12.3456	13.2681	0.9305	0.3536
DUMMY_200910	-172.1537	35.1662	-4.8954	0.0000
DUMMY_200911	147.3989	35.1666	4.1914	0.0000
DUMMY_201701	-116.5462	34.8638	-3.3429	0.0010
DUMMY_201705	-238.2123	34.8676	-6.8319	0.0000
DUMMY_201706	195.3182	34.8850	5.5989	0.0000
DUMMY_201708	204.5318	34.8713	5.8653	0.0000
DUMMY_201903	-331.6614	35.1412	-9.4380	0.0000
DUMMY_201904	162.2998	35.1383	4.6189	0.0000
DUMMY_201911	-75.6592	35.2157	-2.1485	0.0333
DUMMY_202003	-70.7965	35.5392	-1.9921	0.0482
DUMMY_202004	-83.9048	35.3196	-2.3756	0.0188

R-squared	0.7137	Mean dependent var	-35.0398
Adjusted R-squared	0.6682	S.D. dependent var	58.2972
S.E. of regression	33.5784	Akaike info criterion	9.9965
Sum squared resid	170,253.4000	Schwarz criterion	10.4469
Log likelihood	-854.6944	Hannan-Quinn criter.	10.1792
F-statistic	15.6871	Durbin-Watson stat	1.1461
Prob(F-statistic)	0.0000		

The D_ indicates the first difference
Last sample observation is August 2020, first forecast period is September 2020
SCEMFGEMP(-3) indicates SCE manufacturing employment lagging 3 months

Other Public Authority Customer Model

Dependent Variable: D(OPACUS)
Method: Least Squares
Sample: 2006M01 2020M08
Included observations: 176

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-43.8637	6.1685	-7.1109	0.0000
D(SCEGOVEMP(-12))	0.5076	0.4988	1.0176	0.3104
JAN	9.8328	9.8155	1.0018	0.3180
FEB	0.0273	9.1074	0.0030	0.9976
MAR	-10.1698	9.1181	-1.1153	0.2664
APR	-2.7475	7.1206	-0.3859	0.7001
MAY	-0.2370	8.0001	-0.0296	0.9764
JUN	5.4096	6.8386	0.7910	0.4301
JUL	31.5267	39.1636	0.8050	0.4221
AUG	2.8090	7.2352	0.3882	0.6984
SEP	-17.2947	19.3828	-0.8923	0.3736
OCT	-18.4401	19.8085	-0.9309	0.3533
NOV	6.3581	9.5754	0.6640	0.5077
DUMMY_201701	-778.3387	17.9986	-43.2445	0.0000
DUMMY_201705	-1,459.0260	18.0347	-80.9009	0.0000
DUMMY_201706	1,075.1680	18.0688	59.5043	0.0000
DUMMY_201708	1,151.2480	18.0828	63.6655	0.0000
DUMMY_201903	-451.1207	18.0387	-25.0086	0.0000
DUMMY_201904	57.0701	18.0398	3.1636	0.0019
DUMMY_201905	382.4062	18.0971	21.1308	0.0000
OPATREND	0.1113	0.0267	4.1702	0.0001

R-squared	0.9918	Mean dependent var	-28.0284
Adjusted R-squared	0.9907	S.D. dependent var	179.6170
S.E. of regression	17.3142	Akaike info criterion	8.6525
Sum squared resid	46,466.2800	Schwarz criterion	9.0308
Log likelihood	-740.4210	Hannan-Quinn criter.	8.8059
F-statistic	933.9161	Durbin-Watson stat	2.0956
Prob(F-statistic)	0.0000		

The D_ indicates the first difference
Last sample observation is August 2020, first forecast period is September 2020
SCEGOVEMP_COVID(-12) indicates SCE government employment lagging 12 months

Agriculture Customer Model

Dependent Variable: D(AGCUS)
Method: Least Squares
Sample: 2004M01 2020M08
Included observations: 200

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	48.8297	63.0450	0.7745	0.4396
D(AGEMP(-24))	9.3321	7.7614	1.2024	0.2308
JAN	-44.3517	45.1383	-0.9826	0.3271
FEB	-71.4420	84.5855	-0.8446	0.3994
MAR	-110.5420	97.8284	-1.1300	0.2600
APR	-210.7301	190.9026	-1.1039	0.2711
MAY	-116.5455	127.8050	-0.9119	0.3630
JUN	-52.7682	65.4653	-0.8060	0.4213
JUL	31.4665	29.6955	1.0596	0.2907
AUG	5.8476	28.4390	0.2056	0.8373
SEP	-62.1573	66.9466	-0.9285	0.3544
OCT	-61.7098	53.9849	-1.1431	0.2545
NOV	-35.9878	36.3583	-0.9898	0.3236
DUMMY_201705	-9,736.1850	43.1243	-225.7704	0.0000
DUMMY_201706	5,487.3640	43.0084	127.5882	0.0000
DUMMY_201708	4,340.7950	42.8436	101.3173	0.0000
DUMMY_201903	-737.5706	43.1021	-17.1122	0.0000
DUMMY_201904	-3,803.2840	45.1334	-84.2676	0.0000
DUMMY_201905	4,466.0470	44.2237	100.9877	0.0000

R-squared	0.9983	Mean dependent var	-10.7450
Adjusted R-squared	0.9981	S.D. dependent var	948.4981
S.E. of regression	41.5563	Akaike info criterion	10.3822
Sum squared resid	312,572.8000	Schwarz criterion	10.6955
Log likelihood	-1,019.2150	Hannan-Quinn criter.	10.5090
F-statistic	5,749.3930	Durbin-Watson stat	2.4356
Prob(F-statistic)	0.0000		

The D_ indicates the first difference
Last sample observation is August 2020, first forecast period is September 2020
AGEMP_COVID(-24) indicates SCE agricultural employment lagging 24 months

Street Light Customer Model

Dependent Variable: D(STLCUS)
Method: Least Squares
Sample: 2008M01 2020M08
Included observations: 152

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	24.8731	14.1104	1.7628	0.0802
D(SCERESCUSF(-21))	-0.0034	0.0015	-2.2186	0.0282
JAN	36.5629	19.5974	1.8657	0.0643
FEB	13.8210	19.0097	0.7271	0.4685
MAR	13.2754	19.0248	0.6978	0.4865
APR	22.9479	19.0041	1.2075	0.2294
MAY	-3.1682	19.1633	-0.1653	0.8689
JUN	15.0091	19.0579	0.7876	0.4323
JUL	-11.2690	19.0644	-0.5911	0.5554
AUG	-32.8138	19.8542	-1.6527	0.1007
SEP	-16.2430	19.3630	-0.8389	0.4030
OCT	0.9786	19.4167	0.0504	0.9599
NOV	-8.1917	19.8536	-0.4126	0.6806
DUMMY_200811	-226.2404	48.4747	-4.6672	0.0000
DUMMY_200908	-290.3963	48.4721	-5.9910	0.0000
DUMMY_201612	-357.2863	48.6357	-7.3462	0.0000
DUMMY_201701	-5,621.8610	48.3033	-116.3868	0.0000
DUMMY_201708	5,912.4930	48.5696	121.7323	0.0000

R-squared	0.9957	Mean dependent var	16.8026
Adjusted R-squared	0.9951	S.D. dependent var	662.6811
S.E. of regression	46.3866	Akaike info criterion	10.6227
Sum squared resid	288,329.7000	Schwarz criterion	10.9808
Log likelihood	-789.3251	Hannan-Quinn criter.	10.7682
F-statistic	1,804.9300	Durbin-Watson stat	2.1603
Prob(F-statistic)	0.0000		

The D_ indicates the first difference
Last sample observation is August 2020, first forecast period is September 2020
SCERESCUSE_COVID(-21) indicates SCE residential customer lagging 21 months

10) Customer Model Variable Description

Residential Customer Models

RESCUS	Recorded number of residential class customers. Source: SCE
LA	Prefix in front of variable name to denote Los Angeles County
OR	Prefix in front of variable name to denote Orange County.
SB	Prefix in front of variable name to denote San Bernardino County.
RV	Prefix in front of variable name to denote Riverside County.
VSB	Prefix in front of variable name to denote Ventura and Santa Barbara Counties.
OTH	Prefix in front of variable name to denote Rural Counties (Fresno, Inyo, Kern Kings, Mono and Tulare)
Jan-Nov	Binary variable set equal to 1 for the designated month and zero otherwise.
DUMMY_YYYYMMMM	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in customer data.
DUMMYCRASH	Binary variables equal to one during the housing crash, and zero otherwise, that are designed to capture recessionary period.
GEOSTRT	SCE housing starts. Compiled from Moody's Analytics data.

Commercial Customer Models

ComCus	Recorded number of commercial class customers. Source: SCE
DUMMY_YYYYMMMM	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in customer data.
Jan-Nov	Binary variable set equal to 1 for the designated month and zero otherwise.

Industrial Customer Model

INDCUS	Recorded number of industrial class customers. Source: SCE
SCEGOVEMP	SCE regional government employment. Compiled from Moody's Analytics data.
INDTREND_FLAT	Linear counter variable designed to capture secular trend growth not otherwise captured in the model.

DUMMY_YYYYMMMM	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in customer data.
Jan-Nov	Binary variable set equal to 1 for the designated month and zero otherwise.

Other Public Authorities Customer Model

OPACUS	Recorded number of other public authority class customers. Source: SCE
SCEGOVEMP	SCE regional government employment. Compiled from Moody's Analytics data.
DUMMY_YYYYMMMM	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in customer data.
Jan-Nov	Binary variable set equal to 1 for the designated month and zero otherwise.

Agriculture Customer Model

AGCUS	Recorded number of agriculture class customers. Source: SCE
AGEMP	Number of persons employed in agriculture. Source: SCE estimate
.	
DUMMY_YYYYMMMM	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in customer data.
Jan-Nov	Binary variable set equal to 1 for the designated month and zero otherwise.

Street Light Customer Model

STRCUS	Recorded number of street lighting customers. Source: SCE
DUMMY_YYYYMMMM	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in customer data.
Jan-Nov	Binary variable set equal to 1 for the designated month and zero otherwise.

Additional Forecast Detail

Forecast Calibration Procedures

See discussion above on how SCE load forecasts are prepared.

Economic and Demographic Data

SCE incorporates economic and demographic historical and demographic data from Moody's Analytics, IHS Markit, and Dodge Data.

Historical Peak and Projected Peak Loads

Historical and projected peak loads are measured at SCE's system level. The historical mean of maximum effective temperatures in the past 20 years are considered as normal peak weather used for weather normalized historical peak and future 1-in-2 weather assumption. Load-weather sensitivity are model coefficients run by 24 hourly regressions as a function of day of the week, weekend/holiday, month, season, and temp using hourly system load data from 2011-2020. Future DER incremental impacts are added into the base hourly load forecasts.

Energy and Peak Loss Estimates

SCE's loss factor estimates are from SCE's internal distribution/transmission loss calculation study. A three-year (2018-2020) average of load history from meter, ISO, and generation levels was used to estimate the network energy loss. The meter level data came from the monthly billing usage of bundled, CCA, and DA customers, and ISO usage came from CAISO settlement hourly load from smart meter data, Generation level load is from the system hourly load readings. The loss factor is calculated from the Channel 1 usage without NEM load netted out.

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

The forecast assumes full DA subscription under the proposed lifting of the statewide DA cap starting January 1, 2021 (The Final Decision for Increased Limits for Direct Access Transactions in Rulemaking (R.)19-03-009)). SCE does not have a forecast for Residential and Non-residential monthly peak load. SCE assumes the operational CCA aggregations for 2022 as well as operational CCAs by the end of 2021 listed to the right based on information available as of April 2, 2020.

SCE forecasts the new 2022 CCA load through multiple steps. First, SCE generates the weather normalized monthly energy (MWh) forecasts for each new CCA based on the number of active CCA customers at the end of 2020 for active CCAs and a 10% opt-rate assumption for new CCAs. SCE applies the weather normalization analysis by sector (e.g. residential, commercial, industrial, etc.) from its retail level to each CCA's historical (2018) monthly energy based on each CCA's customer mix. Next, SCE applies its forecasted retail sales growth rate between 2020 and 2022 to the CCA monthly load to generate the 2022 monthly energy forecast for each CCA. In addition, SCE adjusts the monthly energy forecast to reflect each CCA's phase-in period. Lastly, SCE calculates the monthly peak for each CCA by applying the average load factor from averaging the load factors of the top 3 peak days from the available number of yearly hourly load for each CCA (one to four years).

SCE develops its aggregated bundled load forecast as a residual of SCE's retail sales forecast subtracted by SCE's aggregated DA and CCA load forecast. SCE's methods for forecasting its retail sales and aggregated DA load is provided to CEC through its recent 2020 IEPR Demand Forms.

SCE generates its aggregated CCA load generally through multiple steps. First, SCE generates the annual energy forecast for the aggregated CCA load based on historical CCA load and combining its existing CCA load and the new 2022 CCA load. SCE applies the similar weather normalization and energy growth rate based on its retail sales forecast. Second, SCE applies its existing aggregated bundled portfolio hourly profiles to the annual CCA energy forecast to derive its hourly aggregated CCA load forecast for 2022. Lastly, SCE establishes its monthly peak forecast for the aggregated CCA load using the maximum load of the hourly CCA load forecast for each month.

Weather Adjustment Procedures

See discussion above on SCE's weather adjustment procedures.

Hourly Loads by Subarea

See 4 FINAL PUBLIC Attachment A.xlsx for longitude and latitude details for SCE A-banks.

Climate Change

SCE reflected climate change impacts on load by using the CED 2019 Hourly Results - SCE - MID-MID forecast.

Known Load Growth Projects

SCE incorporated information on proposed commercial cannabis cultivation that are determined to have a high likelihood of starting operations in the near-term period (one-to-two years). For the 2021 IEPR forecast, SCE used aggregated load (GWh) and peak (MW) estimates from approximately 250 to 275 proposed commercial cultivation projects.

Other Load Modifier Impacts

SCE incorporated estimates of commercial cannabis cultivation peak demand as a load modifier as shown on Demand Form 3,