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SCE 2019 IEPR Sales Forecast Methods and Models 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.

Direct Access and Community Choice Aggregate

As a result of recent legislation, SCE is expecting the existing DA cap to be increased by the end of 2022. As a result, two increases in 2021 and 2022 in DA load are reflected in the forecast. 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 (RMEA) in 2018. SCE includes the 2019 start of CPA Phases 3 and 4 in the forecast. Starting in 2021, 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

[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.

had received at the time that this forecast was made. As a result, SCE's bundled sales growth has been reduced relative to retail sales growth compared to earlier forecasts.

2) Forecast Assumptions and Drivers

The underlying assumptions regarding the economy, weather, electricity prices, conservation and self-generation 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 4.5,

Weather

SCE uses 30 year average temperature conditions to characterize normal weather. Normal 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 week end 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 --0.21 to -0.09. 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 0.7 to 2.0. 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 293,153 operational residential and non-residential behind-the-meter solar systems at the end of 2018 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 bypass capacity and annual capacity factors. The capacity factors are taken from the CPUC Self-Generation Incentive Program, Fifth Year Impact Evaluation, Draft-Final Report prepared by in February 2007 by Itron for PG&E and the Self-Generation Incentive Working Group. 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.

Residential 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.

As this model is 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 of future zero-net energy home policy. Compliance rates under new policies Title 24 will be 100% starting 2020. From 2018 to 2022, the annual incremental adoptions are decreased by 2.35% to reflect the effect of the implementation of the existing NEM 2.0. 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 cut by half under future NEM 3.0. As a result, the annual incremental solar adoptions are reduced by 9.6% due to NEM 3.0 from years 2023 to 2030.

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 all major customer or rate groups 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 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 for each customer groups. First, SCE converts the bill savings estimates from SAM model into the maximum market potential for each customer

[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 2017 U.S. PV Market Outlook data set, Bloomberg New Energy Finance, June 1 2017.

group based on SCE's internal analysis. Next, SCE runs a Bass Diffusion Model with estimated maximum market potential and other specified parameters to produce annual adoptions forecast for each customer group. SCE finally aggregates the adoptions forecast by two major categories: the paired systems and the stand alone systems. The two categories are further broken down to residential and the non-residential sectors. SCE specifies the representative storage system size for each customer group based on historical installation statistics. The SAM model simulates 8760 hourly storage system dispatch profile for each customer group.

Transportation Electrification

SCE forecasts future transportation electrification load growth for both light duty EV load and other non-light duty electric transportation load. As a nascent and dynamic market, EV load is affected by multiple drivers such as manufacturer supply, policies set by Federal, state, and local governments, and electric vehicle technology advancement. SCE models plug-in electric vehicle (PEV) load forecast separately as a positive load contributor.

SCE models the light duty EV through a Generalized Bass Diffusion model. The SCE model estimates the impact from Total Cost of Ownership (TCO) for EVs relative to the TCO of internal combustion engines. The SCE model also considers the impact from customers' range anxiety effect using CEC's average vehicle range forecast as its explanatory variable.[5] In addition, SCE utilizes American Community Survey (ACS) to estimate the maximum potential for future likely EV adopters.[6]

Once EV population numbers are determined for each year, several factors are then applied to determine hourly, daily, and annual EV load shapes.[7]

--Building Electrification

SCE derived its building electrification load assumption from its economy-wide PATHWAYS GHG scenario analysis results regarding the optimal level of electrification of 30% residential space and water heating pumps and 30% commercial space heating in California by 2030.

SCE's internal total cost of ownership model residential space and water heating projections were used as these reflect internal view on consumer choices in new home purchases and retrofit replacements, and how these choices change over time with projected increased policy support.

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.

Other EX Post Modifications to the Sales Forecast

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[5] Bahrenian, Aniss, Jesse Gage, Sudhakar Konala, Bob McBride, Mark Palmere, Charles Smith, and Ysbrand van der Werf. 2017. Transportation Energy Demand Forecast, 2018-2030. California Energy Commission. Publication Number: CEC-200-2017-010.

[6] https://www.census.gov/programs-surveys/acs/

[7] SCE develops assumptions for electric vehicle miles traveled per day (eVMT), vehicle-type mix (e.g., battery electric 100, battery electric 250, plug-in hybrid 20 and plug-in hybrid 50), vehicle and charger efficiencies, customer TOU adoption, and customer charging behavior.

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:

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

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

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 is 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 2017Q4 sales forecast compared to actual weather adjusted monthly sales for the period January 2018 to December 2018 reveals the following:

SCE Sales Forecast Evaluation for 2018

Month	Actual (Weather Adj.) MWh	Forecast Winter 2016 Vintage MWh	MAPE Calculation
Jan-18	6,895,474	6,754,777	0.0206
Feb-18	5,662,858	5,909,468	0.0426
Mar-18	6,881,557	6,533,656	0.0519
Apr-18	5,758,331	6,135,119	0.0634
May-18	6,279,129	6,276,991	0.0003
Jun-18	6,911,354	6,995,463	0.0121
Jul-18	7,845,056	7,712,111	0.0171
Aug-18	8,951,117	8,384,509	0.0654
Sep-18	8,070,415	7,982,475	0.0110
Oct-18	7,471,806	7,252,530	0.0298
Nov-18	6,518,175	6,318,682	0.0311
Dec-18	6,707,409	7,005,579	0.0435

Jan-Dec Total (GWh)	83,953	83,261
Simple Error - Jan-Dec	-0.5%	
MAPE Error: Jan-Dec	3.2%	

The analysis shows that the 2018 SCE billed monthly retail sales often tracked actual weather-adjusted retail sales closely for most of the year. The yearly MAPE was 3.2 percent.

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:

$$Y_t = x_t' \beta + e_t$$

where e_t is an independent, and identically distributed, mean zero random disturbance, and β 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 deviate from the true coefficients β 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

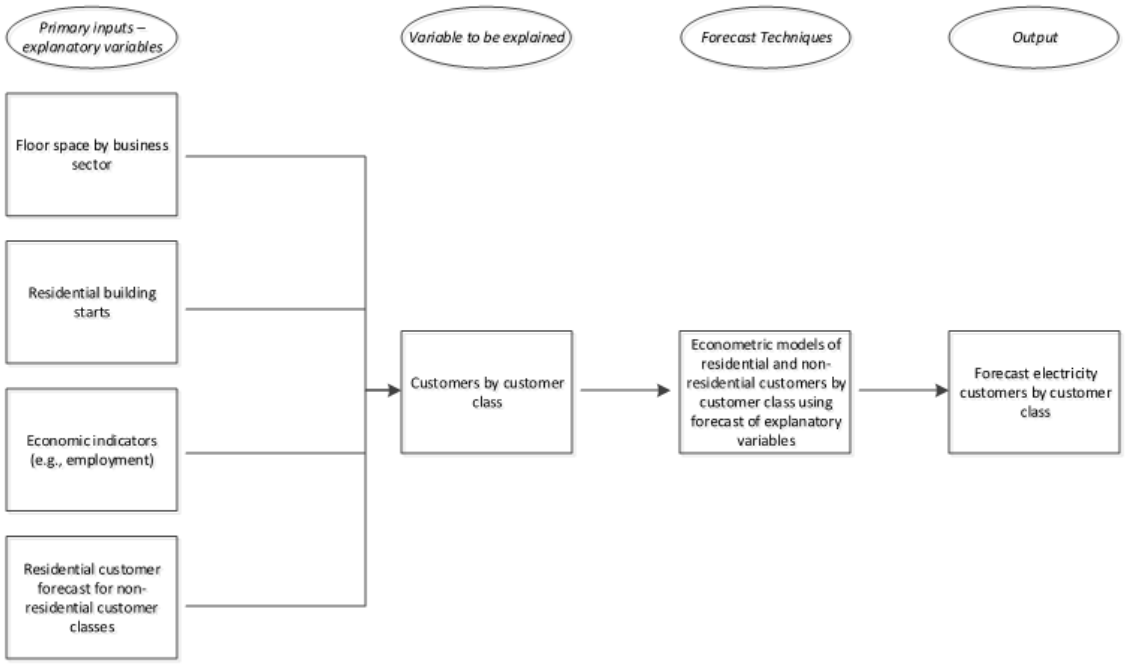
The variability of forecasts is measured by the forecast standard errors. For a single equation without lagged dependent variables or ARMA terms, the forecast standard errors are computed as:

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

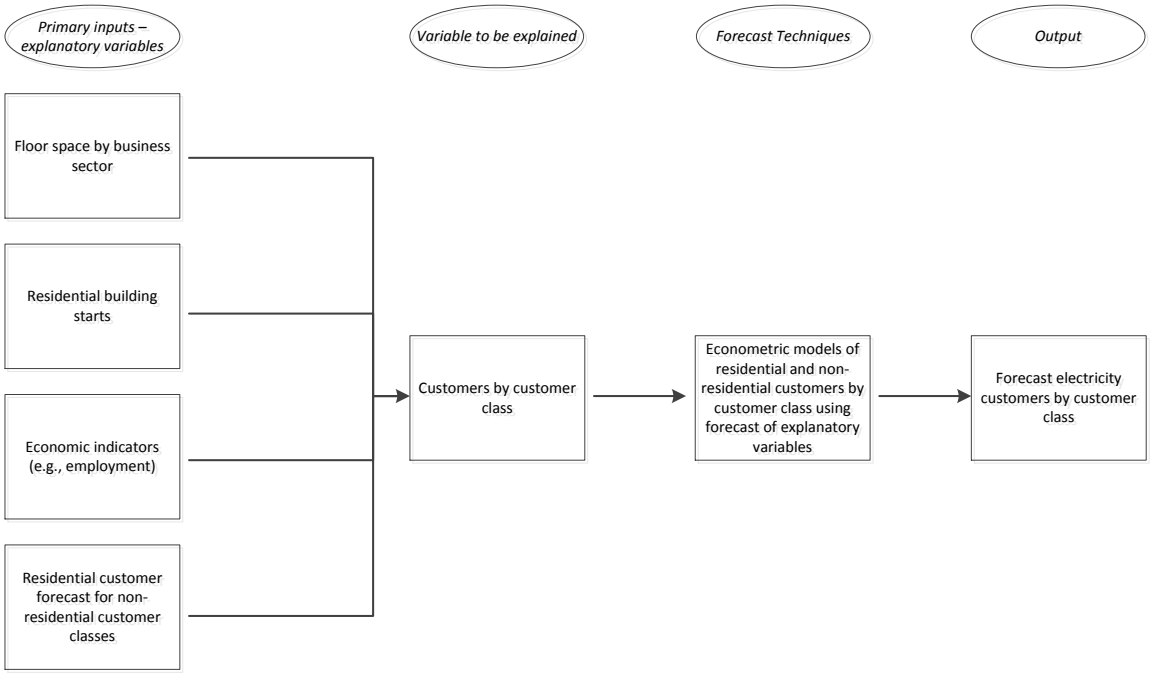
where S is the standard error of regression. These standard errors account for both innovation uncertainty (the first term) and coefficient uncertainty (the second term). Point forecasts made from linear regression models estimated by least squares are optimal in the sense that they have the smallest 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

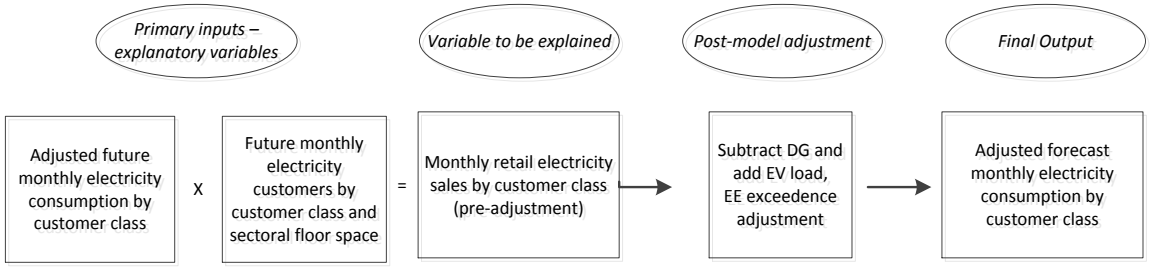
Electricity Consumption (kWh per Customer) Modeling and Forecasting



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

Number of Observations Read	176
Number of Observations Used	176

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	1.28587	0.07144	114.89	<.0001
Error	157	0.09762	0.00062181		
Corrected Total	175	1.3835			

Root MSE	0.02494	R-Square	0.9294
Dependent Mean	0.52817	Adj R-Sq	0.9213
Coeff Var	4.72124		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-0.43315	0.37689	-1.15	0.2522
RES_LACDD_SUMSEAS_LASIZE	1	7.17E-07	5.14E-08	13.95	<.0001
RES_LAHDD_WINSEAS_LASIZE	1	2.42E-07	3.83E-08	6.33	<.0001
CUMBDAYS	1	0.00016654	0.00008902	1.87	0.0632
LOGLAGDP24	1	0.16895	0.07257	2.33	0.0212
RES_RATE	1	-0.40117	0.31266	-1.28	0.2013
RES_CAC	1	-0.21747	0.08084	-2.69	0.0079
DUMMY_201808	1	0.11872	0.02727	4.35	<.0001
JAN	1	0.00153	0.01011	0.15	0.8797
FEB	1	-0.08157	0.01312	-6.22	<.0001
MAR	1	-0.02574	0.00936	-2.75	0.0067
APR	1	-0.0512	0.01166	-4.39	<.0001
MAY	1	-0.0334	0.01537	-2.17	0.0312
JUN	1	-0.00294	0.01512	-0.19	0.8463
JUL	1	0.00863	0.01828	0.47	0.6374
AUG	1	0.03092	0.01968	1.57	0.1182
SEP	1	-0.00698	0.02049	-0.34	0.7338
OCT	1	-0.0183	0.01674	-1.09	0.2759
NOV	1	-0.0357	0.01321	-2.7	0.0076

LOGLAGDP24 indicates the log of Los Angeles County GDP lagged 24 periods.
Last sample observation was September 2018. First forecast period was October 2018.

Residential Electricity Use Model – Orange County

Dependent Variable: ORUSE

Number of Observations Read	176
Number of Observations Used	176

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	1.09554	0.06086	62.43	<.0001
Error	157	0.15306	0.00097491		
Corrected Total	175	1.2486			

Root MSE	0.03122	R-Square	0.8774
Dependent Mean	0.56039	Adj R-Sq	0.8634
Coeff Var	5.5718		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.13612	0.22922	0.59	0.5535
RES_ORCDD_SUMSEAS_ORSIZE	1	6.81E-07	6.15E-08	11.08	<.0001
RES_ORHDD_WINSEAS_ORSIZE	1	1.87E-07	4.87E-08	3.84	0.0002
CUMBDAYS	1	0.00019665	0.00011132	1.77	0.0793
LOGORGDP24	1	0.12232	0.0548	2.23	0.027
RES_RATE	1	-0.3345	0.39793	-0.84	0.4018
RES_CAC	1	-0.32451	0.07524	-4.31	<.0001
UMMY_201808	1	0.12309	0.03424	3.6	0.0004
JAN	1	-0.00238	0.01301	-0.18	0.8549
FEB	1	-0.09943	0.01656	-6	<.0001
MAR	1	-0.04069	0.01168	-3.48	0.0006
APR	1	-0.07281	0.01358	-5.36	<.0001
MAY	1	-0.05785	0.0167	-3.46	0.0007
JUN	1	-0.02024	0.01587	-1.28	0.2041
JUL	1	0.01557	0.01708	0.91	0.3635
AUG	1	0.04971	0.01841	2.7	0.0077
SEP	1	0.00885	0.02012	0.44	0.6608
OCT	1	-0.02405	0.01801	-1.34	0.1837
NOV	1	-0.05056	0.01581	-3.2	0.0017

LOGORGDP24 indicates the log of Orange County GDP lagged 24 months.
Last sample observation was September 2018. First forecast period was October 2018.

Residential Electricity Use Model – Riverside County

Dependent Variable: RVUSE

Number of Observations Read	176
Number of Observations Used	176

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	19	9.0967	0.47877	298.29	<.0001
Error	156	0.25039	0.00161		
Corrected Total	175	9.34709			

Root MSE	0.04006	R-Square	0.9732
Dependent Mean	0.76964	Adj R-Sq	0.9699
Coeff Var	5.20545		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-0.19515	0.21571	-0.9	0.367
RES_RIVCDD_SUMSEAS_RVSIZE	1	8.47E-07	5.77E-08	14.68	<.0001
RES_RIVHDD_WINSEAS_RVSIZE	1	9.41E-08	4.67E-08	2.02	0.0455
CUMBDAYS	1	0.0001928	0.00014351	1.34	0.1811
LOGRVGDP6	1	0.25327	0.04955	5.11	<.0001
RES_RATE	1	-1.06934	0.47234	-2.26	0.025
RES_CAC	1	-0.22815	0.063	-3.62	0.0004
DUMMY_200508	1	-0.16769	0.0418	-4.01	<.0001
UMMY_201808	1	0.11208	0.04421	2.54	0.0122
JAN	1	0.0219	0.01653	1.32	0.1871
FEB	1	-0.08957	0.02109	-4.25	<.0001
MAR	1	-0.01846	0.01519	-1.22	0.2261
APR	1	-0.0368	0.01957	-1.88	0.0619
MAY	1	-0.07478	0.02528	-2.96	0.0036
JUN	1	-0.03512	0.02785	-1.26	0.2092
JUL	1	0.00887	0.03962	0.22	0.8232
AUG	1	0.08718	0.04321	2.02	0.0453
SEP	1	-0.00512	0.04275	-0.12	0.9048
OCT	1	-0.05477	0.03029	-1.81	0.0725
NOV	1	-0.02584	0.0217	-1.19	0.2356

LOGRVGDP6 indicates the log of Riverside County GDP lagged six periods.
Last sample observation was September 2018. First forecast period was October 2018.

Residential Electricity Use Model – San Bernardino County

Dependent Variable: SBUSE

Number of Observations Read	164
Number of Observations Used	164

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	4.65482	0.2586	241.81	<.0001
Error	145	0.15507	0.00107		
Corrected Total	163	4.80989			

Root MSE	0.0327	R-Square	0.9678
Dependent Mean	0.63767	Adj R-Sq	0.9638
Coeff Var	5.12845		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.03643	0.20604	0.18	0.8599
RES_SBCDD_SUMSEAS_SBSIZE	1	7.76E-07	5.34E-08	14.52	<.0001
RES_SBHDD_WINSEAS_SBSIZE	1	1.81E-07	4.17E-08	4.33	<.0001
CUMBDAYS	1	0.00021389	0.00012472	1.72	0.0885
LOGSBGDP3	1	0.13719	0.04119	3.33	0.0011
RES_RATE	1	-0.78922	0.45104	-1.75	0.0823
RES_CAC	1	-0.14074	0.05301	-2.66	0.0088
UMMY_201808	1	0.10634	0.03609	2.95	0.0037
JAN	1	-0.00463	0.01408	-0.33	0.7425
FEB	1	-0.0942	0.01799	-5.24	<.0001
MAR	1	-0.03021	0.01277	-2.37	0.0193
APR	1	-0.05096	0.01643	-3.1	0.0023
MAY	1	-0.03616	0.0223	-1.62	0.107
JUN	1	0.0035	0.02314	0.15	0.8801
JUL	1	0.03642	0.03144	1.16	0.2486
AUG	1	0.0806	0.03381	2.38	0.0184
SEP	1	0.02096	0.03376	0.62	0.5356
OCT	1	-0.00916	0.02523	-0.36	0.7169
NOV	1	-0.03177	0.0185	-1.72	0.088

LOGSBGDP3 indicates the log of San Bernardino County GDP lagged three months.
Last sample observation was September 2018. First forecast period was October 2018.

Residential Electricity Use Model – Ventura/Santa Barbara Counties

Dependent Variable: VSBUSE

Number of Observations Read	152
Number of Observations Used	152

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	21	0.5336	0.02541	45.77	<.0001
Error	130	0.07217	0.00055517		
Corrected Total	151	0.60577			

Root MSE	0.02356	R-Square	0.8809
Dependent Mean	0.56032	Adj R-Sq	0.8616
Coeff Var	4.20512		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.27278	0.48407	0.56	0.5741
RES_SBVENCDD_SUMSEAS_VENSIZE	1	4.83E-07	5.28E-08	9.15	<.0001
RES_SBVENHDD_WINSEAS_VENSIZE	1	2.23E-07	3.40E-08	6.56	<.0001
CUMBDAYS	1	0.00024437	0.00009702	2.52	0.013
LOGVSBGDP24	1	0.09186	0.11047	0.83	0.4072
RES_RATE	1	-0.36299	0.72648	-0.5	0.6182
RES_CAC	1	-0.22714	0.08832	-2.57	0.0112
DUMMY_200812	1	0.05976	0.02536	2.36	0.0199
DUMMY_201411	1	-0.05927	0.02477	-2.39	0.0182
DUMMY_201601	1	-0.06728	0.02534	-2.65	0.0089
DUMMY_201808	1	0.12023	0.02593	4.64	<.0001
JAN	1	0.00443	0.01045	0.42	0.6726
FEB	1	-0.08273	0.01406	-5.88	<.0001
MAR	1	-0.0384	0.00969	-3.96	0.0001
APR	1	-0.05856	0.01172	-5	<.0001
MAY	1	-0.03451	0.01493	-2.31	0.0224
JUN	1	-0.01349	0.01454	-0.93	0.3553
JUL	1	-0.00647	0.01731	-0.37	0.7092
AUG	1	0.00476	0.01834	0.26	0.7955
SEP	1	-0.02804	0.02025	-1.38	0.1685
OCT	1	-0.01901	0.01677	-1.13	0.2591
NOV	1	-0.03513	0.01345	-2.61	0.0101

LOGVSBGDP24 indicates the log of Ventura/Santa Barbara counties GDP lagged 24 periods.
Last sample observation was September 2018. First forecast period was October 2018.

Residential Electricity Use Model – Other (Rural) Counties

Dependent Variable: OTHUSE

Number of Observations Read	176
Number of Observations Used	176

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	5.31766	0.29543	297.85	<.0001
Error	157	0.15572	0.00099186		
Corrected Total	175	5.47339			

Root MSE	0.03149	R-Square	0.9715
Dependent Mean	0.66251	Adj R-Sq	0.9683
Coeff Var	4.7537		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.23045	0.14136	1.63	0.1051
RES_OTHCDD_SUMSEAS_OTHSIZE	1	7.34E-07	4.89E-08	15	<.0001
RES_OTHHDD_WINSEAS_OTHSIZE	1	1.77E-07	3.70E-08	4.77	<.0001
CUMBDAYS	1	0.00016937	0.00011238	1.51	0.1338
LOGOTHGDP3	1	0.1422	0.05094	2.79	0.0059
RES_RATE	1	-0.96641	0.37757	-2.56	0.0114
RES_CAC	1	-0.13197	0.06158	-2.14	0.0337
DUMMY_201209	1	-0.10365	0.03357	-3.09	0.0024
JAN	1	0.01509	0.01347	1.12	0.2644
FEB	1	-0.07805	0.0165	-4.73	<.0001
MAR	1	-0.00547	0.01396	-0.39	0.6956
APR	1	-0.02716	0.02043	-1.33	0.1857
MAY	1	-0.0042	0.02932	-0.14	0.8863
JUN	1	0.03584	0.03134	1.14	0.2546
JUL	1	0.03555	0.04055	0.88	0.382
AUG	1	0.06742	0.04214	1.6	0.1116
SEP	1	0.01804	0.03782	0.48	0.634
OCT	1	0.01013	0.03028	0.33	0.7384
NOV	1	-0.04113	0.02127	-1.93	0.055

LOGOTHGDP3 indicates the log of Other/rural counties GDP lagged three months.
Last sample observation was September 2018. First forecast period was October 2018.

Commercial Electricity Use Model

Dependent Variable: COMUSE

Number of Observations Read	128
Number of Observations Used	128

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	42.60982	2.66311	43.4	<.0001
Error	111	6.81087	0.06136		
Corrected Total	127	49.42069			

Root MSE	0.24771	R-Square	0.8622
Dependent Mean	6.381	Adj R-Sq	0.8423
Coeff Var	3.88196		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-17.60147	4.24957	-4.14	<.0001
COMCDD_SUMSEAS_COMSIZE	1	7.05E-07	2.21E-07	3.19	0.0018
CUMBDAYS	1	0.0012	0.00113	1.06	0.2896
LOGSCEGDP3	1	4.3954	0.79835	5.51	<.0001
DUMMY_201808	1	0.42634	0.28388	1.5	0.136
NONRES_CAC	1	-7.15066	1.47526	-4.85	<.0001
JAN	1	-0.4087	0.10844	-3.77	0.0003
FEB	1	-0.80176	0.15528	-5.16	<.0001
MAR	1	-0.206	0.10848	-1.9	0.0602
APR	1	-0.23316	0.12623	-1.85	0.0674
MAY	1	-0.20296	0.12362	-1.64	0.1035
JUN	1	0.12158	0.12299	0.99	0.325
JUL	1	0.18144	0.18648	0.97	0.3327
AUG	1	0.42935	0.20855	2.06	0.0419
SEP	1	0.1489	0.23011	0.65	0.5189
OCT	1	0.18927	0.16253	1.16	0.2467
NOV	1	-0.34898	0.13121	-2.66	0.009

LOGSCEGDP3 indicates the log of SCE GDP lagged three periods.
Last sample observation was September 2018. First forecast period was October 2018.

Industrial Electricity Use Model

Dependent Variable: INDUSE

Number of Observations Read	128
Number of Observations Used	128

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	6.25669	0.39104	25.11	<.0001
Error	111	1.72891	0.01558		
Corrected Total	127	7.98559			

Root MSE	0.1248	R-Square	0.7835
Dependent Mean	2.58059	Adj R-Sq	0.7523
Coeff Var	4.83622		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	3.58371	0.43997	8.15	<.0001
COMCDD_SUMSEAS	1	0.00069489	0.00045325	1.53	0.1281
CUMBDAYS	1	0.00048305	0.00056656	0.85	0.3957
INDRATE15	1	-0.0615	0.01837	-3.35	0.0011
INDTREND	1	-0.00604	0.00044883	-13.46	<.0001
DUMMY_201808	1	0.08587	0.14249	0.6	0.548
JAN	1	-0.12947	0.05456	-2.37	0.0194
FEB	1	-0.17003	0.0781	-2.18	0.0316
MAR	1	-0.04322	0.05464	-0.79	0.4307
APR	1	-0.01986	0.06358	-0.31	0.7554
MAY	1	0.02316	0.06225	0.37	0.7106
JUN	1	0.07886	0.0618	1.28	0.2046
JUL	1	0.05472	0.09296	0.59	0.5573
AUG	1	0.1623	0.10385	1.56	0.121
SEP	1	-0.04704	0.11453	-0.41	0.6821
OCT	1	0.02214	0.08127	0.27	0.7858

INDRATE15 indicates SCE industrial rates lagged 15 months.
Last sample observation was September 2018. First forecast period was October 2018.

Other Public Authority Electricity Use Model

Dependent Variable: OPAUSE

Number of Observations Read	104
Number of Observations Used	104

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	2.35053	0.13058	35.94	<.0001
Error	85	0.30888	0.00363		
Corrected Total	103	2.65941			

Root MSE	0.06028	R-Square	0.8839
Dependent Mean	1.31377	Adj R-Sq	0.8593
Coeff Var	4.58847		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-2.96453	2.03617	-1.46	0.1491
COMCDD	1	0.00044969	0.0002364	1.9	0.0605
NONRES_CAC	1	-1.53692	1.37763	-1.12	0.2677
OPARATE18	1	-0.00827	0.01011	-0.82	0.4156
LOGSCEGOVEMP9	1	0.84871	0.27947	3.04	0.0032
CUMBDAYS	1	0.00019364	0.00036238	0.53	0.5945
LIGHTINDEX_ADJ	1	-0.10384	0.18928	-0.55	0.5847
DUMMY_201808	1	0.11293	0.07187	1.57	0.1198
JAN	1	-0.13015	0.02948	-4.41	<.0001
FEB	1	-0.18544	0.04635	-4	0.0001
MAR	1	-0.02515	0.02939	-0.86	0.3946
APR	1	0.02489	0.042	0.59	0.5551
MAY	1	0.08867	0.03964	2.24	0.0279
JUN	1	0.13724	0.03393	4.04	0.0001
JUL	1	0.08129	0.04785	1.7	0.093
AUG	1	0.17264	0.05401	3.2	0.002
SEP	1	0.16266	0.05997	2.71	0.0081
OCT	1	0.16193	0.04298	3.77	0.0003
NOV	1	-0.03089	0.03609	-0.86	0.3944

OPARATE18 indicates SCE OPA rate lagged 18 months.
LOGSCEGOVEMP9 indicates a log of SCE government employment lagged nine months.
Last sample observation was September 2018. First forecast period was October 2018.

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Agriculture Electricity Use Model

Dependent Variable: AGUSE

Number of Observations Read	128
Number of Observations Used	128

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	19	781.68603	41.14137	90.8	<.0001
Error	108	48.93612	0.45311		
Corrected Total	127	830.62215			

Root MSE	0.67314	R-Square	0.9411
Dependent Mean	6.24376	Adj R-Sq	0.9307
Coeff Var	10.78094		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-37.71629	7.04115	-5.36	<.0001
CUMBDAYS	1	0.0027	0.00305	0.89	0.3767
PRECIPITATION9	1	-0.08146	0.0716	-1.14	0.2578
LOGSCEGDP3	1	5.72191	0.97179	5.89	<.0001
RUNOFF	1	-0.00427	0.00052989	-8.06	<.0001
DUMMY_201705	1	4.77742	0.73269	6.52	<.0001
DUMMY_201706	1	2.90571	0.76898	3.78	0.0003
DUMMY_201707	1	2.75581	0.79013	3.49	0.0007
AGDUMMY2012_2017	1	0.92662	0.13753	6.74	<.0001
JAN	1	-0.56068	0.29471	-1.9	0.0598
FEB	1	-0.48556	0.43151	-1.13	0.263
MAR	1	0.58441	0.3077	1.9	0.0602
APR	1	1.9482	0.36239	5.38	<.0001
MAY	1	3.28766	0.36517	9	<.0001
JUN	1	5.23407	0.35651	14.68	<.0001
JUL	1	6.39111	0.34532	18.51	<.0001
AUG	1	6.00454	0.31478	19.08	<.0001
SEP	1	4.35234	0.33462	13.01	<.0001
OCT	1	2.79396	0.32573	8.58	<.0001
NOV	1	0.69493	0.35648	1.95	0.0538

PRECIPITATION9 indicates precipitation lagged 9 months.
LOGSCEGDP3 indicates a log of SCE GDP lagged three months.
Last sample observation was September 2018. First forecast period was October 2018.

Street Light Electricity Use Model

Dependent Variable: STLUSE

Number of Observations Read	128
Number of Observations Used	128

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	12.84442	3.21111	210.99	<.0001
Error	123	1.87197	0.01522		
Corrected Total	127	14.71639			

Root MSE	0.12337	R-Square	0.8728
Dependent Mean	2.9081	Adj R-Sq	0.8687
Coeff Var	4.24217		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.213	0.24615	0.87	0.3885
CUMBDAYS	1	0.0005146	0.0003234	1.59	0.1141
RESPRSTRLT	1	0.01055	0.0003686	28.62	<.0001
DAYHRS	1	-0.00056239	0.0002219	-2.53	0.0125
LIGHTINDX	1	-0.30907	0.04739	-6.52	<.0001

Last sample observation was September 2018. First forecast period was October 2018.

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
CUMBDAYS	Average number of days in monthly billing statement multiplied by the number of billing cycles in month. Source: SCE
GeoGDP	Regional output in 2009 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
COMRATE	Commercial class constant $2009 dollar price of electricity in cents per kWh. Sources: IHS Global Insight and SCE
SCEGDP	SCE regional output in 2009 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
NONRES_CAC	An index measuring the average efficiency of commercial air conditioning equipment. Compiled from Energy Information Administration data.
COMCUSDUMMY	Binary variables equal to one on multiple periods, and zero otherwise, that are designed to capture irregularities in customer 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 $2009 dollar price of electricity in cents per kWh. Sources: SCE and IHS Global Insight
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
INDUSE_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 $2009 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
DAYSHRS	Number of hours of daylight in a month in Southern California (a proxy for office lighting use). 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.
NONRES_CAC	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
PRECIP	Fresno monthly precipitation level in inches. Sources: National Oceanic and Atmospheric Administration and SCE
JAN-NOV	Binary variable set equal to 1 for the designated month and zero otherwise.
AGRDUMMY1217	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.
DAYSHRS	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

Number of Observations Read	164
Number of Observations Used	164

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	67403670	4212729	14.3	<.0001
Error	147	43292696	294508		
Corrected Total	163	110696366			

Root MSE	542.68604	R-Square	0.6089
Dependent Mean	399.20122	Adj R-Sq	0.5663
Coeff Var	135.94298		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-21.4145	181.60589	-0.12	0.9063
LASTRT	1	0.01516	0.00718	2.11	0.0365
DUMMY_201707	1	-4568.1931	564.03225	-8.1	<.0001
DUMMY_201708	1	4628.6805	563.48112	8.21	<.0001
DUMMY_REC0803	1	-3225.85485	565.24483	-5.71	<.0001
DUMMY_REC0804	1	3280.78926	565.62774	5.8	<.0001
JAN	1	343.3571	209.0696	1.64	0.1027
FEB	1	481.74727	209.06787	2.3	0.0226
MAR	1	362.01579	212.86275	1.7	0.0911
APR	1	267.60531	212.86505	1.26	0.2107
MAY	1	40.72958	209.10412	0.19	0.8458
JUN	1	71.38841	209.10297	0.34	0.7333
JUL	1	71.59872	212.88325	0.34	0.7371
AUG	1	27.73619	212.89365	0.13	0.8965
SEP	1	311.66305	212.86167	1.46	0.1453
OCT	1	225.75949	212.86328	1.06	0.2906
NOV	1	159.09712	212.86174	0.75	0.456

The D_ indicates the first difference.
Last sample observation was September 2018. First forecast period was October 2018.

Residential Electricity Customer Model – Orange County

Dependent Variable: D_ORCUS

Number of Observations Read	152
Number of Observations Used	152

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	37398629	2077702	17.8	<.0001
Error	133	15521051	116700		
Corrected Total	151	52919680			

Root MSE	341.61328	R-Square	0.7067
Dependent Mean	465.10526	Adj R-Sq	0.667
Coeff Var	73.44859		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	145.90361	114.84793	1.27	0.2062
ORSTRT12	1	0.04202	0.00963	4.37	<.0001
DUMMY_201705	1	-1420.90031	361.89577	-3.93	0.0001
DUMMY_201706	1	937.18288	359.80316	2.6	0.0102
DUMMY_201707	1	-3639.00864	357.42648	-10.18	<.0001
DUMMY_201708	1	3626.87862	356.32084	10.18	<.0001
DUMMY_2018_03	1	-1617.53823	355.9503	-4.54	<.0001
DUMMY_2018_04	1	2091.28482	356.15451	5.87	<.0001
JAN	1	26.12406	136.76446	0.19	0.8488
FEB	1	26.21208	136.79543	0.19	0.8483
MAR	1	81.38633	139.52192	0.58	0.5607
APR	1	26.54022	139.56798	0.19	0.8495
MAY	1	30.83276	139.48122	0.22	0.8254
JUN	1	-46.33107	139.47743	-0.33	0.7403
JUL	1	112.29009	139.46899	0.81	0.4222
AUG	1	15.55122	139.46331	0.11	0.9114
SEP	1	40.37416	139.46487	0.29	0.7727
OCT	1	132.66906	139.46593	0.95	0.3432
NOV	1	155.25585	139.4643	1.11	0.2676

The D_ indicates the first difference.
OCSTRT12 denotes Orange County total starts lagged 12 periods.
Last sample observation was September 2018. First forecast period was October 2018.

Residential Electricity Customer Model – Riverside County

Dependent Variable: D_RVCUS

Number of Observations Read	128
Number of Observations Used	128

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	22	19724364	896562	12.45	<.0001
Error	105	7560139	72001		
Corrected Total	127	27284503			

Root MSE	268.33062	R-Square	0.7229
Dependent Mean	447.34375	Adj R-Sq	0.6649
Coeff Var	59.98309		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	263.26376	109.17847	2.41	0.0176
RVSTRT3	1	0.02851	0.01574	1.81	0.0729
DUMMYCRASH	1	-197.79652	82.7896	-2.39	0.0187
DUMMY_201202	1	687.12704	283.50514	2.42	0.0171
DUMMY_201206	1	-1096.45468	284.82659	-3.85	0.0002
DUMMY_201207	1	802.65796	284.39633	2.82	0.0057
DUMMY_201705	1	-1568.51562	282.26833	-5.56	<.0001
DUMMY_201706	1	1265.81157	284.51242	4.45	<.0001
DUMMY_201707	1	-1687.20793	287.28925	-5.87	<.0001
DUMMY_201708	1	2121.9333	289.475	7.33	<.0001
DUMMY_2018_03	1	-1786.771	286.92804	-6.23	<.0001
DUMMY_2018_04	1	1460.39714	289.09914	5.05	<.0001
JAN	1	18.22094	117.39821	0.16	0.877
FEB	1	88.64955	120.35248	0.74	0.463
MAR	1	96.0568	120.00453	0.8	0.4253
APR	1	21.60765	120.00193	0.18	0.8575
MAY	1	31.7096	120.05292	0.26	0.7922
JUN	1	99.42592	123.43329	0.81	0.4223
JUL	1	162.34627	123.35865	1.32	0.191
AUG	1	-17.12925	120.00151	-0.14	0.8868
SEP	1	82.33061	120.00127	0.69	0.4942
OCT	1	44.58759	120.00562	0.37	0.711
NOV	1	196.30003	120.00903	1.64	0.1049

The D_ indicates the first difference.
RVSTRT3 denotes Riverside County total starts lagged 3 periods.
Last sample observation was September 2018. First forecast period was October 2018.

Residential Electricity Customer Model – San Bernardino County

Dependent Variable: D_SBCUS

Number of Observations Read	128
Number of Observations Used	128

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	22	15465107	702959	9.69	<.0001
Error	105	7618968	72562		
Corrected Total	127	23084075			

Root MSE	269.37261	R-Square	0.6699
Dependent Mean	327.99219	Adj R-Sq	0.6008
Coeff Var	82.12775		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	45.5044	109.48554	0.42	0.6785
SBSTRT3	1	0.03907	0.01718	2.27	0.025
DUMMYCRASH	1	-289.62499	83.20402	-3.48	0.0007
DUMMY_201206	1	-1273.79381	285.9187	-4.46	<.0001
DUMMY_201207	1	1055.54239	285.48929	3.7	0.0003
DUMMY_201704	1	583.53171	285.51139	2.04	0.0435
DUMMY_201705	1	-1612.08662	283.36555	-5.69	<.0001
DUMMY_201706	1	1018.70712	285.61761	3.57	0.0005
DUMMY_201707	1	-1100.58877	288.39869	-3.82	0.0002
DUMMY_201708	1	1254.28906	290.58131	4.32	<.0001
DUMMY_2018_03	1	-1173.82977	288.03199	-4.08	<.0001
DUMMY_2018_04	1	1382.06911	292.27347	4.73	<.0001
JAN	1	196.50469	117.85375	1.67	0.0984
FEB	1	273.87094	117.86197	2.32	0.0221
MAR	1	200.83377	120.47052	1.67	0.0985
APR	1	254.46241	123.8153	2.06	0.0423
MAY	1	110.16442	120.51892	0.91	0.3628
JUN	1	133.01906	123.91178	1.07	0.2855
JUL	1	120.69456	123.83722	0.97	0.332
AUG	1	80.21769	120.46751	0.67	0.5069
SEP	1	90.83552	120.46727	0.75	0.4525
OCT	1	170.07354	120.47162	1.41	0.161
NOV	1	45.34365	120.47503	0.38	0.7074

The D_ indicates the first difference.
SBSTRT3 indicates San Bernardino County starts lagged three periods.
Last sample observation was September 2018. First forecast period was October 2018.

Residential Electricity Customer Model – Ventura/Santa Barbara Counties

Dependent Variable: D_VSBCUS

Number of Observations Read	128
Number of Observations Used	128

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	19	6489719	341564	18.9	<.0001
Error	108	1951446	18069		
Corrected Total	127	8441165			

Root MSE	134.42076	R-Square	0.7688
Dependent Mean	101.02344	Adj R-Sq	0.7281
Coeff Var	133.05899		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	37.74274	44.8646	0.84	0.4021
VSBSTRT12	1	0.14285	0.07836	1.82	0.0711
DUMMY_201503	1	575.43232	141.72722	4.06	<.0001
DUMMY_201706	1	376.83299	142.7497	2.64	0.0095
DUMMY_201707	1	-1330.82493	141.38581	-9.41	<.0001
DUMMY_201708	1	1143.45145	141.32885	8.09	<.0001
DUMMY_201712	1	-516.43367	141.9453	-3.64	0.0004
DUMMY_2018_03	1	-832.89959	142.05742	-5.86	<.0001
DUMMY_2018_04	1	969.57858	144.17579	6.72	<.0001
JAN	1	87.43744	60.43008	1.45	0.1508
FEB	1	82.09972	60.42661	1.36	0.1771
MAR	1	2.55559	63.37714	0.04	0.9679
APR	1	83.05881	61.837	1.34	0.182
MAY	1	14.67775	60.42375	0.24	0.8085
JUN	1	-192.13071	61.76222	-3.11	0.0024
JUL	1	184.40953	61.78397	2.98	0.0035
AUG	1	81.19764	61.86765	1.31	0.1922
SEP	1	190.63988	61.77114	3.09	0.0026
OCT	1	93.17342	61.76255	1.51	0.1343
NOV	1	82.11226	61.7623	1.33	0.1865

The D_ indicates the first difference.
VSBSTRT12 indicates Ventura/Santa Barbara Counties starts lagged 12 periods.
Last sample observation was September 2018. First forecast period was October 2018.

Residential Electricity Customer Model – Other (Rural) Counties

Dependent Variable: D_OTHCUS

Number of Observations Read	128
Number of Observations Used	128

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	20	2371607	118580	11.55	<.0001
Error	107	1098735	10269		
Corrected Total	127	3470342			

Root MSE	101.33386	R-Square	0.6834
Dependent Mean	119.55469	Adj R-Sq	0.6242
Coeff Var	84.75942		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-1.18718	45.12677	-0.03	0.9791
OTHSTRT3	1	0.07501	0.02211	3.39	0.001
DUMMY_201704	1	355.84699	107.09548	3.32	0.0012
DUMMY_201705	1	-517.95187	106.29028	-4.87	<.0001
DUMMY_201706	1	385.99206	106.28737	3.63	0.0004
DUMMY_201707	1	-334.41782	106.29977	-3.15	0.0021
DUMMY_201708	1	448.08212	106.28539	4.22	<.0001
DUMMY_201709	1	-271.80234	106.86979	-2.54	0.0124
DUMMY_2018_03	1	-745.55735	106.55706	-7	<.0001
DUMMY_2018_04	1	773.73438	108.05543	7.16	<.0001
JAN	1	17.69992	44.36476	0.4	0.6907
FEB	1	2.04487	44.37921	0.05	0.9633
MAR	1	13.20119	45.39037	0.29	0.7717
APR	1	30.52999	46.58082	0.66	0.5136
MAY	1	25.71144	45.49456	0.57	0.5732
JUN	1	3.4771	45.60138	0.08	0.9394
JUL	1	-60.01603	45.6928	-1.31	0.1918
AUG	1	-22.33881	45.67503	-0.49	0.6258
SEP	1	46.62162	46.6054	1	0.3194
OCT	1	-35.09956	45.33172	-0.77	0.4405
NOV	1	-2.15984	45.31808	-0.05	0.9621

The D_ indicates the first difference.
OTHSTRT3 indicates Other/Rural Counties starts lagged three periods.
Last sample observation was September 2018. First forecast period was October 2018.

Commercial Customer Model

Dependent Variable: D_COMCUS

Number of Observations Read	128
Number of Observations Used	128

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	63775098	3751476	62.05	<.0001
Error	110	6650684	60461		
Corrected Total	127	70425781			

Root MSE	245.8877	R-Square	0.9056
Dependent Mean	302.21094	Adj R-Sq	0.891
Coeff Var	81.36294		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	143.41435	78.76466	1.82	0.0714
D_SCERESCUSF	1	0.03286	0.01051	3.13	0.0023
DUMMY_201701	1	-1603.2503	259.96148	-6.17	<.0001
DUMMY_201705	1	-5163.68094	268.43686	-19.24	<.0001
DUMMY_201706	1	3747.85152	265.98323	14.09	<.0001
DUMMY_201708	1	3247.1488	295.85398	10.98	<.0001
DUMMY_201709	1	-332.45859	260.70698	-1.28	0.2049
JAN	1	-77.83625	110.1309	-0.71	0.4812
FEB	1	154.20283	108.10174	1.43	0.1566
MAR	1	169.85903	107.43609	1.58	0.1167
APR	1	133.29619	109.09517	1.22	0.2244
MAY	1	107.65717	110.15654	0.98	0.3306
JUN	1	273.87376	110.00259	2.49	0.0143
JUL	1	147.35713	107.44696	1.37	0.173
AUG	1	82.82391	109.98037	0.75	0.453
SEP	1	73.42931	113.41733	0.65	0.5187
OCT	1	90.44212	110.27953	0.82	0.4139
NOV	1	21.40551	110.20561	0.19	0.8464

The D_ indicates the first difference.
SCERESCUS indicates SCE residential customers.
Last sample observation was September 2018. First forecast period was October 2018.

Industrial Customer Model

Dependent Variable: D_INDCUS

Number of Observations Read	128
Number of Observations Used	128

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	19	275430	14496	15.71	<.0001
Error	108	99643	922.62281		
Corrected Total	127	375073			

Root MSE	30.37471	R-Square	0.7343
Dependent Mean	-29.78906	Adj R-Sq	0.6876
Coeff Var	-101.96597		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-56.22502	12.03991	-4.67	<.0001
D_SCEGOVEMP12	1	4.71996	1.18491	3.98	0.0001
INDTREND_FLAT18	1	0.3115	0.08658	3.6	0.0005
DUMMY_200910	1	-161.94364	32.73605	-4.95	<.0001
DUMMY_200911	1	163.12895	32.51921	5.02	<.0001
DUMMY_201701	1	-136.71975	32.14471	-4.25	<.0001
DUMMY_201705	1	-253.66306	32.12686	-7.9	<.0001
DUMMY_201706	1	185.905	32.1415	5.78	<.0001
DUMMY_201708	1	209.34708	32.20747	6.5	<.0001
JAN	1	23.54291	13.78508	1.71	0.0905
FEB	1	9.72861	13.29597	0.73	0.4659
MAR	1	20.51411	13.27402	1.55	0.1252
APR	1	-13.15115	15.4622	-0.85	0.3969
MAY	1	18.38066	13.72399	1.34	0.1833
JUN	1	25.40164	13.62574	1.86	0.065
JUL	1	16.55909	13.27629	1.25	0.215
AUG	1	5.16129	13.91976	0.37	0.7115
SEP	1	5.48163	13.90782	0.39	0.6943
OCT	1	20.30329	14.11116	1.44	0.1531
NOV	1	11.52371	13.99532	0.82	0.4121

The D_ indicates the first difference.
SCEGOVEMP12 indicates SCE manufacturing employment lagged 12 periods.
Last sample observation was September 2018. First forecast period was October 2018.

Other Public Authority Customer Model

Dependent Variable: D_OPACUS

Number of Observations Read	152
Number of Observations Used	152

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	5233835	327115	926.52	<.0001
Error	135	47663	353.05718		
Corrected Total	151	5281498			

Root MSE	18.78982	R-Square	0.991
Dependent Mean	-29.49342	Adj R-Sq	0.9899
Coeff Var	-63.7085		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-29.90757	5.75524	-5.2	<.0001
D_SCEMFGEMP3	1	0.61679	0.54539	1.13	0.2601
DUMMY_201701	1	-773.45813	19.57873	-39.51	<.0001
DUMMY_201705	1	-1451.29675	19.57254	-74.15	<.0001
DUMMY_201706	1	1080.82572	19.72726	54.79	<.0001
DUMMY_201708	1	1156.31531	19.7383	58.58	<.0001
JAN	1	9.94299	9.05577	1.1	0.2742
FEB	1	-1.84903	10.47225	-0.18	0.8601
MAR	1	-12.026	10.58173	-1.14	0.2578
APR	1	-3.56954	8.38541	-0.43	0.671
MAY	1	-2.13511	9.14718	-0.23	0.8158
JUN	1	6.65593	7.94108	0.84	0.4034
JUL	1	37.7176	41.04669	0.92	0.3598
AUG	1	6.53203	7.74614	0.84	0.4006
SEP	1	-20.18321	19.2902	-1.05	0.2973
OCT	1	-24.57666	23.60245	-1.04	0.2996
NOV	1	5.29912	10.70899	0.49	0.6215

The D_ indicates the first difference.
SCEMFGMP3 indicates SCE manufacturing employment lagged 3 periods.
Last sample observation was September 2018. First forecast period was October 2018.

Agriculture Customer Model

Dependent Variable: D_AGCUS

Number of Observations Read	152
Number of Observations Used	152

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	143626304	8976644	4998.79	<.0001
Error	135	242428	1795.76173		
Corrected Total	151	143868732			

Root MSE	42.37643	R-Square	0.9983
Dependent Mean	-8.34211	Adj R-Sq	0.9981
Coeff Var	-507.98243		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	56.58795	73.20282	0.77	0.4409
DAGEMP24	1	10.52419	9.98275	1.05	0.2937
DUMMY_201703	1	-162.66659	44.17925	-3.68	0.0003
DUMMY_201705	1	-9742.96013	44.46764	-219.1	<.0001
DUMMY_201706	1	5488.29121	44.40968	123.58	<.0001
DUMMY_201708	1	4336.65501	44.11148	98.31	<.0001
JAN	1	-42.89916	53.07141	-0.81	0.4203
FEB	1	-73.76347	90.50717	-0.82	0.4165
MAR	1	-120.94465	132.4567	-0.91	0.3628
APR	1	-243.69692	245.71861	-0.99	0.3231
MAY	1	-139.68959	167.07468	-0.84	0.4046
JUN	1	-53.37372	67.81144	-0.79	0.4326
JUL	1	50.0151	59.64615	0.84	0.4032
AUG	1	13.84314	25.20437	0.55	0.5838
SEP	1	-68.66175	77.21032	-0.89	0.3754
OCT	1	-71.94785	63.15277	-1.14	0.2566
NOV	1	-35.70234	34.89839	-1.02	0.3081

The D_ indicates the first difference.
AGREMP24 indicates SCE agricultural employment lagged 24 periods.
Last sample observation was September 2018. First forecast period was October 2018.

Street Light Customer Model

Dependent Variable: D_STLCUS

Number of Observations Read	128
Number of Observations Used	128

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	65864192	4116512	1895.31	<.0001
Error	111	241086	2171.94648		
Corrected Total	127	66105278			

Root MSE	46.60415	R-Square	0.9964
Dependent Mean	20.32813	Adj R-Sq	0.9958
Coeff Var	229.25945		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-4.60676	14.94301	-0.31	0.7584
DSCERESCUS18	1	0.00407	0.00287	1.42	0.1584
DUMMY_200811	1	-233.40061	49.27819	-4.74	<.0001
DUMMY_200908	1	-295.74148	49.38228	-5.99	<.0001
DUMMY_201701	1	-5607.54214	48.89278	-114.69	<.0001
DUMMY_201708	1	5884.42538	49.23579	119.52	<.0001
JAN	1	35.97772	21.31227	1.69	0.0942
FEB	1	36.52466	20.50258	1.78	0.0776
MAR	1	34.52554	20.94082	1.65	0.102
APR	1	32.11528	20.60141	1.56	0.1219
MAY	1	16.28969	20.6022	0.79	0.4308
JUN	1	28.55819	20.39525	1.4	0.1642
JUL	1	10.74793	20.64225	0.52	0.6036
AUG	1	-5.85342	21.94859	-0.27	0.7902
SEP	1	16.83741	21.13299	0.8	0.4273
OCT	1	15.65719	20.98256	0.75	0.4571
NOV	1	4.41251	21.56074	0.2	0.8382

The D_ indicates the first difference.
SCERESCUS18 indicates SCE residential customers lagged 18 periods.
Last sample observation was September 2017. First forecast period was October 2017.

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.
GEOCUSDUMMY	Binary variables equal to one on multiple periods, and zero otherwise, that are designed to capture irregularities in customer data.
DUMMY_CRASH0708	Binary variables equal to one during the housing crash, and zero otherwise, that are designed to capture recessionary period.
DUMMY_REC0809	Binary variables equal to one during the Great Recession, and zero otherwise, that are designed to capture recessionary period.

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.
COMLCUSDUMMY	Binary variables equal to one on multiple periods, and zero otherwise, that are designed to capture irregularities in customer data.
DUMMY_REC0809	Binary variables equal to one during the Great Recession, and zero otherwise, that are designed to capture recessionary period.
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.
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
SCEMFGEMP	SCE regional manufacture 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.

11) Model Statistics – Residential Meter Connection Models

Dependent Variable: RESMETER

Number of Observations Read	396
Number of Observations Used	128
Number of Observations with Missing Values	268

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	14	38089259	2720661	20.97	<.0001
Error	113	14657253	129710		
Corrected Total	127	52746512			

Root MSE	360.15302	R-Square	0.7221
Dependent Mean	2104.44531	Adj R-Sq	0.6877
Coeff Var	17.11392		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1165.87736	187.29587	6.22	<.0001
SCESTRT6	1	0.04705	0.00295	15.97	<.0001
SCEMULTISHARE6	1	-1155.54463	322.85621	-3.58	0.0005
JAN	1	-130.57481	157.44278	-0.83	0.4087
FEB	1	-330.59404	157.41407	-2.1	0.0379
MAR	1	-82.62135	157.44823	-0.52	0.6008
APR	1	-289.82759	157.56138	-1.84	0.0685
MAY	1	-61.37577	157.70612	-0.39	0.6979
JUN	1	71.83059	157.72483	0.46	0.6497
JUL	1	-184.33985	157.65459	-1.17	0.2448
AUG	1	-1.62704	157.56214	-0.01	0.9918
SEP	1	-101.35136	161.17215	-0.63	0.5307
OCT	1	7.37678	161.14115	0.05	0.9636
NOV	1	-153.69108	161.11754	-0.95	0.3422
DUMMY_REC0809	1	525.35316	83.32818	6.3	<.0001

SCESTRT6 indicates SCE housing starts lagged 6 periods.
SCEMULTISHARE6 indicates SCE multi-family to single family housing start ration lagged 6 periods.
Last sample observation was September 2018. First forecast period was October 2018.

12) Residential Meter Connection Model Variable Description

RESMETER	Recorded number of new residential meter connections. Source: SCE
RESMETERF	Forecast of new residential meter connections.
SCESTRT	Total housing starts. Compiled from Moody's Analytics data.
SCEMULTISHARE	Ratio of Multifamily housing starts to single family housing starts. 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.