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Docket Number:	17-IEPR-03
Project Title:	Electricity and Natural Gas Demand Forecast
TN #:	217147
Document Title:	2017 IEPR SCE Demand Forecast Form 4
Description:	N/A
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Organization:	Southern California Edison Company
Submitter Role:	Applicant
Submission Date:	4/18/2017 9:59:29 AM
Docketed Date:	4/18/2017

SCE 2017 IEPR Retail Sales and Customer Forecast Methodology

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

By the end of 2013, DA reopening to non-residential customers was completed. In the near term, SCE is expecting no near-term increases in DA load. 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) in April 2017. 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. As a result, SCE's bundled sales growth has been reduced relative to retail sales growth.

2) Forecast Assumptions and Drivers

[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.

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 important 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 ~~a~~authority (federal, state, or local government) customer class electricity sales.

The short-run elasticity value for the impact of employment growth on the electricity consumption 8, , and government is about 9.3,.

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 --0.13 to -0.01. 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. This was particularly true during the 2003 to 2007 period – a period of robust economic growth, and the period 2008 to the present, which saw a sharp decline in real output due to high levels of unemployment and depressed real estate prices followed by a mostly modest pace of growth. 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 0.3 to 1.1. We use 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 211,000 operational behind-the-meter solar systems at the end of 2016 ranging in size from 1KW to more than 1,000 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. Changes to building code require that all new houses constructed starting in 2020 be "zero net energy" (ZNE). Additional estimates were performed to account for future PV installation in compliance of this mandate. As some building developers are already starting to implement this mandate, a gradual compliance rate culminating in 90% in 2020 was assumed. SCE's internal new residential meter forecast was used as the basis of the new homes. From 2016 to 2018, the annual incremental adoptions were decreased by 4.55% to reflect the effect of the implementation of a two-tier rate scheme.

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 affected by several exogenous variables such as manufacturer supply, local, state, and federal policy, and technology advancement, plug-in electric vehicle (PEV) forecasting is treated separately as a positive load contributor.

For light duty SCE obtained three forecasts from Navigant (conservative, base, and high) specific to SCE's territory. The forecasts contain EMission FACtors (EMFAC) categories for light-duty automobiles (LDA) and light-duty trucks (LDT1, LDT2). These forecasts were adjusted downward by approximately 20,000 to align with historical

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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] "H1 2016 US PV Market Outlook: Boom Without a Bust." Bloomberg New Energy Finance. June 7 2016.

adoption numbers through 2016 using Polk/DMV registration data. SCE's 2016 Q4 forecast is the resulting adjusted conservative case from Navigant.Once population numbers are determined for each year, several variables are then applied to determine hourly, daily, and annual electricity load shapes.[5]

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

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 PEV charging, other new electric technologies such as high speed rail and other electrified rail transport, shipping port electrification, industrial uses such as electrified forklifts and truck stops.

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 $j = T + 1, T + 2, \ldots, T + h$
Let $S_{F,t}$ represent predicted sales in period t and $S_{N,t}$ represent actual adjusted sales in period t; then:

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

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[5] SCE develops assumptions for electric vehicle miles traveled per day (eVMT), vehicle-type mix (e.g., battery electric, plug-in hybrid 15, plug-in hybrid 40), vehicle and charger efficiencies, customer TOU adoption, and customer charging behavior.

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

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 September 2014 forecast compared to actual weather adjusted monthly sales for the period January 2015 to December 2015 reveals the following:

SCE Sales Forecast Evaluation for 2016

Month	Actual (Weather Adj.) MWh	Forecast Winter 2016 Vintage MWh	MAPE Calculation
Jan-16	7,028,165	6,665,838	0.0529
Feb-16	5,887,654	5,843,190	0.0076
Mar-16	6,695,341	6,407,544	0.0439
Apr-16	5,919,413	5,828,406	0.0155
May-16	6,343,805	6,308,061	0.0057
Jun-16	6,971,280	7,093,595	0.0174
Jul-16	7,907,627	8,163,464	0.0318
Aug-16	8,591,557	8,721,607	0.0150
Sep-16	8,324,931	8,518,524	0.0230
Oct-16	7,217,890	7,564,452	0.0469
Nov-16	6,740,876	6,403,971	0.0513
Dec-16	6,854,597	6,793,541	0.0089
Jan-Dec Total (GWh)	84,483	84,312	
Simple Error		-0.4%	
MAPE Error		2.7%	

The analysis shows that the 2016 SCE billed monthly retail sales tracked actual weather-adjusted retail sales closely for most of the year.The yearly MAPE was 2.7 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:

$$Y_t = x_t' ß + e_t$$

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 deviate 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

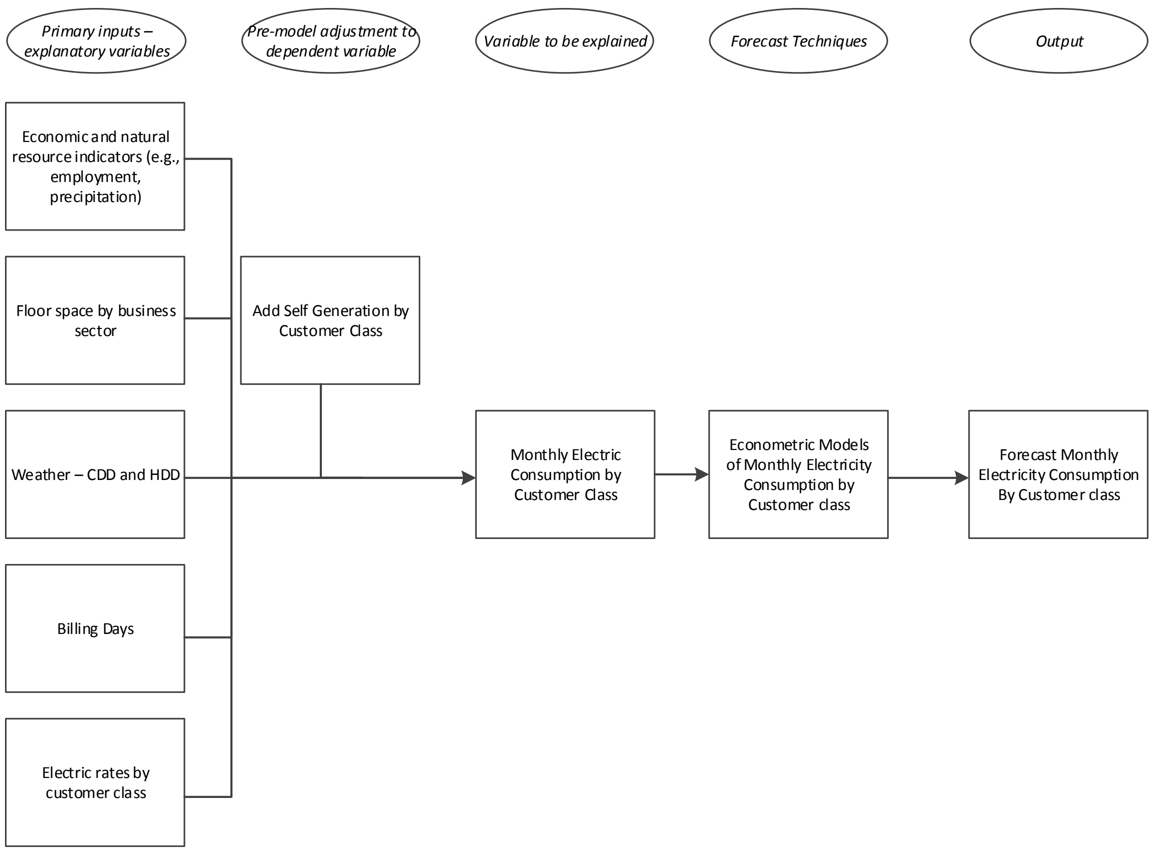
The variability of forecasts is measured by the forecast standard errors. For a single equation without lagged dependent variables or ARMA terms, the forecast standard errors are computed as:

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

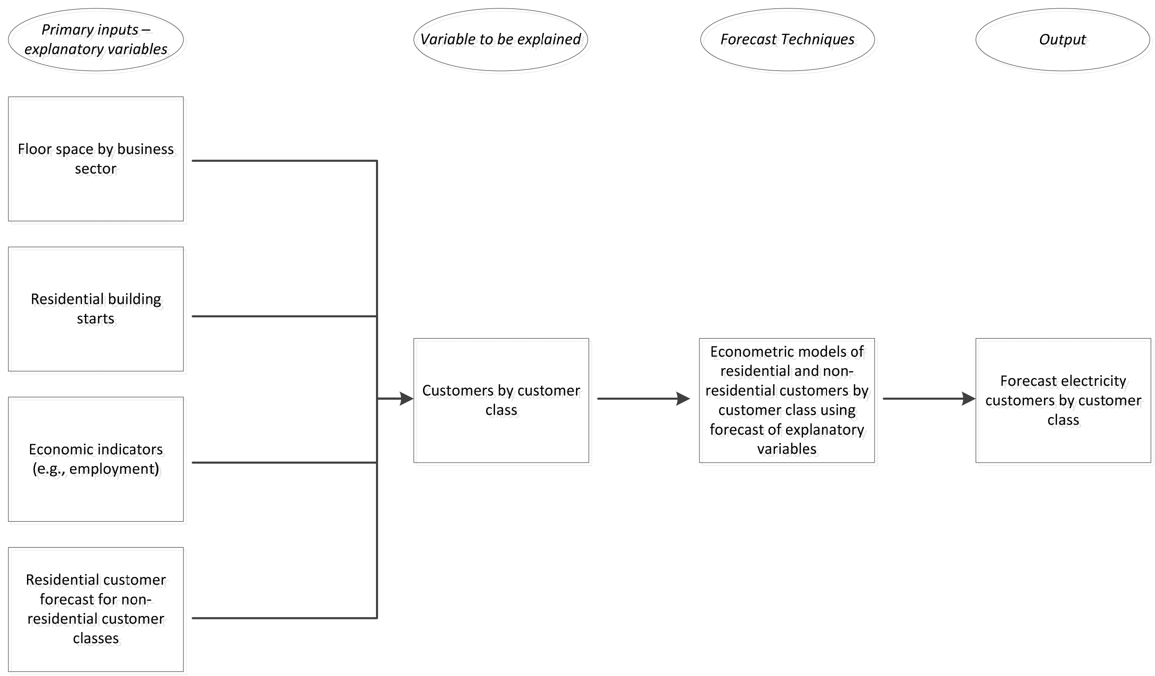
where s is the standard error of regression. These standard errors account for both innovation uncertainty (the first term) and coefficient uncertainty (the second term). Point forecasts made from linear regression models estimated by least squares are optimal in the sense that they have the smallest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

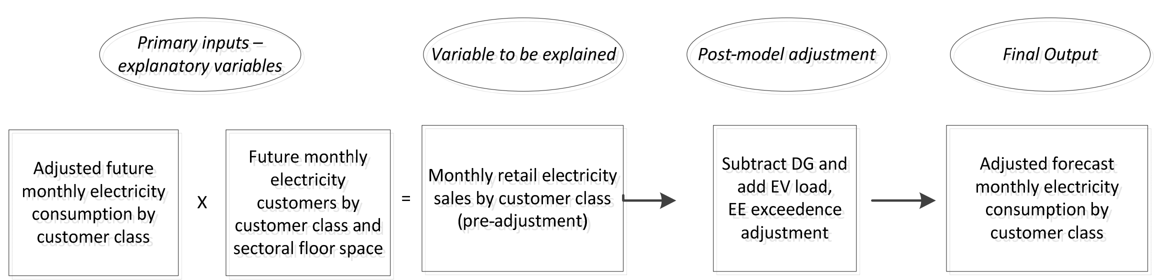
Electricity Consumption (kWh per Customer) Modeling and Forecasting



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

Number of Observations Read	141
Number of Observations Used	141

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	0.95798	0.05322	257.71	<.0001
Error	122	0.0252	0.00020652		
Corrected Total	140	0.98318			

Root MSE	0.01437	R-Square	0.9744
Dependent Mean	0.52904	Adj R-Sq	0.9706
Coeff Var	2.71638		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-0.2472	0.32744	-0.75	0.4517
RES_LACDD_SUMSEAS_LASIZE	1	6.65E-07	3.27E-08	20.33	<.0001
RES_LAHDD_WINSEAS_LASIZE	1	2.11E-07	2.56E-08	8.27	<.0001
CUMBDAYS	1	0.00075195	0.00004964	15.15	<.0001
LOGLAGDP12	1	0.0636	0.05653	1.13	0.2628
RES_RATE	1	-0.00278	0.00211	-1.32	0.1907
RES_CAC	1	-0.14563	0.04281	-3.4	0.0009
DUMMY_201608	1	0.05461	0.01554	3.51	0.0006
JAN	1	0.01732	0.00667	2.6	0.0105
FEB	1	-0.01678	0.00805	-2.09	0.0391
MAR	1	-0.01893	0.00612	-3.09	0.0025
APR	1	-0.02972	0.00719	-4.13	<.0001
MAY	1	-0.01092	0.0101	-1.08	0.2818
JUN	1	0.00289	0.01003	0.29	0.774
JUL	1	0.02724	0.01188	2.29	0.0235
AUG	1	0.03847	0.01275	3.02	0.0031
SEP	1	0.02292	0.01335	1.72	0.0886
OCT	1	0.00372	0.01109	0.34	0.738
NOV	1	0.00649	0.00892	0.73	0.468

LOGLAGDP12 indicates the log of Los Angeles County GDP lagged twelve periods.
Last sample observation was September 2016. First forecast period was October 2016.

Residential Electricity Use Model – Orange County

Number of Observations Read	141
Number of Observations Used	141

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	0.85843	0.04769	120.12	<.0001
Error	122	0.04844	0.00039702		
Corrected Total	140	0.90686			

Root MSE	0.01993	R-Square	0.9466
Dependent Mean	0.56316	Adj R-Sq	0.9387
Coeff Var	3.53817		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-0.42044	0.23632	-1.78	0.0777
RES_ORCDD_SUMSEAS_ORSIZE	1	6.56E-07	4.12E-08	15.9	<.0001
RES_ORHDD_WINSEAS_ORSIZE	1	1.47E-07	3.41E-08	4.31	<.0001
CUMBDAYS	1	0.00088388	0.00006877	12.85	<.0001
LOGORGDP15	1	0.13466	0.04906	2.75	0.007
RES_RATE	1	-0.00163	0.00299	-0.55	0.5862
RES_CAC	1	-0.31679	0.04372	-7.25	<.0001
DUMMY_201608	1	0.08117	0.02133	3.81	0.0002
JAN	1	0.01795	0.0094	1.91	0.0584
FEB	1	-0.02338	0.01128	-2.07	0.0403
MAR	1	-0.03191	0.00843	-3.78	0.0002
APR	1	-0.04545	0.00919	-4.95	<.0001
MAY	1	-0.03324	0.01173	-2.83	0.0054
JUN	1	-0.01536	0.01127	-1.36	0.1753
JUL	1	0.02791	0.01194	2.34	0.0211
AUG	1	0.04633	0.01289	3.59	0.0005
SEP	1	0.03307	0.01397	2.37	0.0195
OCT	1	-0.0033	0.01265	-0.26	0.7949
NOV	1	-0.00299	0.01163	-0.26	0.7975

LOGORGDP15 indicates the log of Orange County GDP lagged 15 months.
Last sample observation was September 2016. First forecast period was October 2016.

Residential Electricity Use Model – Riverside County

Dependent Variable: RVUSE

Number of Observations Read	141
Number of Observations Used	141

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	6.96312	0.38684	347.28	<.0001
Error	122	0.1359	0.00111		
Corrected Total	140	7.09902			

Root MSE	0.03338	R-Square	0.9809
Dependent Mean	0.76791	Adj R-Sq	0.978
Coeff Var	4.34626		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-0.70305	0.2747	-2.56	0.0117
RES_RIVCDD_SUMSEAS_RVSIZE	1	8.12E-07	5.46E-08	14.87	<.0001
RES_RIVHDD_WINSEAS_RVSIZE	1	3.42E-08	4.45E-08	0.77	0.4438
CUMBDAYS	1	0.00107	0.00011514	9.28	<.0001
LOGRVGDP6	1	0.20679	0.06064	3.41	0.0009
RES_RATE	1	-0.004	0.00494	-0.81	0.4201
RES_CAC	1	-0.1973	0.0581	-3.4	0.0009
DUMMY_201608	1	0.06615	0.0364	1.82	0.0716
JAN	1	0.05108	0.01577	3.24	0.0015
FEB	1	0.00901	0.01867	0.48	0.6303
MAR	1	-0.01047	0.01443	-0.73	0.4695
APR	1	-0.01175	0.01764	-0.67	0.5067
MAY	1	-0.04729	0.02403	-1.97	0.0513
JUN	1	-0.03018	0.0265	-1.14	0.257
JUL	1	0.03571	0.03734	0.96	0.3407
AUG	1	0.08175	0.0405	2.02	0.0457
SEP	1	0.03427	0.04085	0.84	0.4032
OCT	1	-0.02533	0.02936	-0.86	0.3901
NOV	1	0.02836	0.0213	1.33	0.1854

LOGRVGDP6 indicates the log of Riverside County GDP lagged six periods.
Last sample observation was September 2016. First forecast period was October 2016.

Residential Electricity Use Model – San Bernardino County

Dependent Variable: sbUSE

Number of Observations Read	141
Number of Observations Used	141

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	3.69574	0.20532	478.91	<.0001
Error	122	0.0523	0.00042873		
Corrected Total	140	3.74804			

Root MSE	0.02071	R-Square	0.986
Dependent Mean	0.6358	Adj R-Sq	0.984
Coeff Var	3.25662		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-0.30502	0.17316	-1.76	0.0807
RES_SBCDD_SUMSEAS_SBSIZE	1	7.34E-07	3.68E-08	19.93	<.0001
RES_SBHDD_WINSEAS_SBSIZE	1	1.25E-07	2.93E-08	4.25	<.0001
CUMBDAYS	1	0.00095805	0.00007146	13.41	<.0001
LOGSBGDP3	1	0.09133	0.03686	2.48	0.0146
RES_RATE	1	-0.00465	0.00306	-1.52	0.1305
RES_CAC	1	-0.13251	0.03514	-3.77	0.0003
DUMMY_201608	1	0.06204	0.02257	2.75	0.0069
JAN	1	0.01916	0.00977	1.96	0.0522
FEB	1	-0.01122	0.01158	-0.97	0.3348
MAR	1	-0.01998	0.00895	-2.23	0.0274
APR	1	-0.02838	0.01106	-2.57	0.0115
MAY	1	-0.02168	0.01596	-1.36	0.1768
JUN	1	0.00257	0.01649	0.16	0.8763
JUL	1	0.05387	0.02165	2.49	0.0142
AUG	1	0.08368	0.0233	3.59	0.0005
SEP	1	0.05323	0.02351	2.26	0.0254
OCT	1	0.00603	0.01803	0.33	0.7387
NOV	1	0.01431	0.01346	1.06	0.2901

LOGSBGDP3 indicates the log of San Bernardino County GDP lagged three months.
Last sample observation was September 2016. First forecast period was October 2016.

Residential Electricity Use Model – Ventura/Santa Barbara Counties

Dependent Variable: VSBUSE

Number of Observations Read	141
Number of Observations Used	141

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	0.46931	0.02607	153.72	<.0001
Error	122	0.02069	0.00016961		
Corrected Total	140	0.49			

Root MSE	0.01302	R-Square	0.9578
Dependent Mean	0.56353	Adj R-Sq	0.9515
Coeff Var	2.31102		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.05796	0.17673	0.33	0.7435
RES_SBVENCDD_SUMSEAS_VENSIZE	1	4.77E-07	2.87E-08	16.59	<.0001
RES_SBVENHDD_WINSEAS_VENSIZE	1	1.58E-07	1.98E-08	7.99	<.0001
CUMBDAYS	1	0.00079924	0.00004498	17.77	<.0001
LOGVSBGDP18	1	0.04142	0.05177	0.8	0.4252
RES_RATE	1	-0.00052008	0.00196	-0.27	0.7914
RES_CAC	1	-0.20234	0.04401	-4.6	<.0001
DUMMY_201608	1	0.03086	0.01391	2.22	0.0284
JAN	1	0.01578	0.00589	2.68	0.0084
FEB	1	-0.0262	0.00729	-3.6	0.0005
MAR	1	-0.02753	0.00551	-5	<.0001
APR	1	-0.04624	0.00617	-7.49	<.0001
MAY	1	-0.03312	0.00868	-3.82	0.0002
JUN	1	-0.02418	0.00851	-2.84	0.0053
JUL	1	-0.01728	0.00964	-1.79	0.0755
AUG	1	-0.01058	0.01029	-1.03	0.3058
SEP	1	-0.02698	0.01107	-2.44	0.0163
OCT	1	-0.02462	0.0095	-2.59	0.0107
NOV	1	-0.00995	0.00777	-1.28	0.2029

LOGVSBGDP6 indicates the log of Ventura/Santa Barbara counties GDP lagged 18 periods.
Last sample observation was September 2016. First forecast period was October 2016.

Residential Electricity Use Model – Other (Rural) Counties

Dependent Variable: OTHUSE

Number of Observations Read	141
Number of Observations Used	141

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	4.04735	0.22485	502.75	<.0001
Error	122	0.05456	0.00044725		
Corrected Total	140	4.10192			

Root MSE	0.02115	R-Square	0.9867
Dependent Mean	0.66253	Adj R-Sq	0.9847
Coeff Var	3.19202		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-0.20068	0.12655	-1.59	0.1154
RES_OTHCDD_SUMSEAS_OTHSIZE	1	6.12E-07	3.79E-08	16.13	<.0001
RES_OTHHDD_WINSEAS_OTHSIZE	1	1.15E-07	2.73E-08	4.23	<.0001
CUMBDAYS	1	0.00092789	0.00007334	12.65	<.0001
LOGOTHGDP3	1	0.10213	0.04279	2.39	0.0185
RES_RATE	1	-0.00551	0.00315	-1.75	0.0823
RES_CAC	1	-0.11556	0.04236	-2.73	0.0073
DUMMY_201608	1	0.04363	0.02304	1.89	0.0607
JAN	1	0.04238	0.01042	4.07	<.0001
FEB	1	0.00354	0.01182	0.3	0.7649
MAR	1	-0.00932	0.01052	-0.89	0.3771
APR	1	-0.01923	0.01437	-1.34	0.1835
MAY	1	-0.00216	0.02144	-0.1	0.9198
JUN	1	0.03618	0.02319	1.56	0.1213
JUL	1	0.08707	0.03026	2.88	0.0047
AUG	1	0.10611	0.03129	3.39	0.0009
SEP	1	0.05942	0.02842	2.09	0.0386
OCT	1	0.01924	0.02245	0.86	0.3933
NOV	1	-0.00371	0.01587	-0.23	0.8156

LOGOTHGDP indicates the log of Other counties GDP lagged three months.
Last sample observation was September 2016. First forecast period was October 2016.

Commercial Electricity Use Model

Dependent Variable: COMUSE

Number of Observations Read	177
Number of Observations Used	177

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	67.82158	4.23885	180.33	<.0001
Error	160	3.76096	0.02351		
Corrected Total	176	71.58255			

Root MSE	0.15332	R-Square	0.9475
Dependent Mean	6.50979	Adj R-Sq	0.9422
Coeff Var	2.35517		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-10.53057	1.8699	-5.63	<.0001
COMCDD_SUMSEAS_COMSIZE	1	7.00E-07	1.08E-07	6.46	<.0001
CUMBDAYS	1	0.00886	0.00047094	18.81	<.0001
LOGSCEGDP	1	2.65881	0.34104	7.8	<.0001
COMRATE24	1	-0.02126	0.0097	-2.19	0.0298
NONRES_CAC	1	-7.13577	0.55566	-12.84	<.0001
JAN	1	-0.19296	0.05741	-3.36	0.001
FEB	1	0.06222	0.07645	0.81	0.4169
MAR	1	0.03474	0.05773	0.6	0.5481
APR	1	0.11569	0.06105	1.89	0.0599
MAY	1	0.22703	0.06428	3.53	0.0005
JUN	1	0.41132	0.0637	6.46	<.0001
JUL	1	0.51098	0.08972	5.7	<.0001
AUG	1	0.80816	0.10335	7.82	<.0001
SEP	1	0.56649	0.10818	5.24	<.0001
OCT	1	0.5894	0.07748	7.61	<.0001
NOV	1	0.30095	0.07087	4.25	<.0001

COMLRATE24 indicates the large commercial rate lagged 24 periods.
LOGSCEGDP indicates the log of SCE GDP.
Last sample observation was September 2016. First forecast period was October 2016.

Industrial Electricity Use Model

Dependent Variable: INDUSE

Number of Observations Read	129
Number of Observations Used	129

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	15	3.86808	0.25787	24.18	<.0001
Error	113	1.20526	0.01067		
Corrected Total	128	5.07334			

Root MSE	0.10328	R-Square	0.7624
Dependent Mean	2.61408	Adj R-Sq	0.7309
Coeff Var	3.95077		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	2.29963	0.31392	7.33	<.0001
COMCDD_SUMSEAS	1	0.00057526	0.00033855	1.7	0.092
CUMBDAYS	1	0.00176	0.00037707	4.67	<.0001
INDRATE24	1	-0.04373	0.01467	-2.98	0.0035
INDTREND	1	-0.00418	0.00034876	-12	<.0001
JAN	1	-0.02941	0.04592	-0.64	0.5231
FEB	1	0.03921	0.05988	0.65	0.5139
MAR	1	0.04974	0.04583	1.09	0.2801
APR	1	0.07702	0.04873	1.58	0.1168
MAY	1	0.14185	0.05082	2.79	0.0062
JUN	1	0.18422	0.05048	3.65	0.0004
JUL	1	0.13066	0.0721	1.81	0.0726
AUG	1	0.23542	0.08005	2.94	0.004
SEP	1	0.05896	0.08717	0.68	0.5002
OCT	1	0.12881	0.06223	2.07	0.0407
NOV	1	0.13771	0.05751	2.39	0.0183

INDRATE24 indicates SCE industrial rates lagged 24 months. Last sample observation was September 2016. First forecast period was October 2016.

Other Public Authority Electricity Use Model

Dependent Variable: OPAUSE

Number of Observations Read	93
Number of Observations Used	93

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	2.34865	0.13816	51.72	<.0001
Error	75	0.20033	0.00267		
Corrected Total	92	2.54899			

Root MSE	0.05168	R-Square	0.9214
Dependent Mean	1.41598	Adj R-Sq	0.9036
Coeff Var	3.64997		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-8.41006	3.2744	-2.57	0.0122
COMCDD	1	0.00050517	0.00022845	2.21	0.0301
NONRES_CAC	1	-3.62579	1.51294	-2.4	0.019
OPARATE12	1	-0.0311	0.01521	-2.04	0.0444
LOGSCEGOVEMP9	1	1.87978	0.4432	4.24	<.0001
CUMBDAYS	1	0.00185	0.00023368	7.92	<.0001
DAYHRS_LIGHTINDX	1	-0.00197	0.00138	-1.43	0.158
JAN	1	-0.02048	0.02892	-0.71	0.481
FEB	1	0.02804	0.03729	0.75	0.4545
MAR	1	0.15082	0.08288	1.82	0.0728
APR	1	0.35883	0.12071	2.97	0.004
MAY	1	0.50313	0.17255	2.92	0.0047
JUN	1	0.4947	0.16822	2.94	0.0044
JUL	1	0.41963	0.18126	2.32	0.0233
AUG	1	0.43039	0.15592	2.76	0.0073
SEP	1	0.40861	0.11214	3.64	0.0005
OCT	1	0.37211	0.07844	4.74	<.0001
NOV	1	0.14399	0.03721	3.87	0.0002

OPARATE12 indicates SCE OPA rate lagged 18 months.
LOGSCEGOVEMP3 indicates a log of SCE government employment lagged nine months.
Last sample observation was September 2016. First forecast period was October 2016.

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Agriculture Electricity Use Model

Dependent Variable: AGUSE

Number of Observations Read	165
Number of Observations Used	165

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	882.64739	55.16546	141.24	<.0001
Error	148	57.80767	0.39059		
Corrected Total	164	940.45507			

Root MSE	0.62497	R-Square	0.9385
Dependent Mean	5.56143	Adj R-Sq	0.9319
Coeff Var	11.23765		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-56.92087	7.1777	-7.93	<.0001
CUMBDAYS	1	0.00918	0.00198	4.64	<.0001
RAINFALL6	1	-0.14924	0.0606	-2.46	0.0149
LOGSCEGDP6	1	7.86241	1.02937	7.64	<.0001
RUNOFF	1	-0.00272	0.00045118	-6.03	<.0001
AGDUMMY20122015	1	1.3318	0.14365	9.27	<.0001
JAN	1	-0.37565	0.24368	-1.54	0.1253
FEB	1	0.21288	0.32436	0.66	0.5127
MAR	1	0.57935	0.24732	2.34	0.0205
APR	1	2.16265	0.27046	8	<.0001
MAY	1	3.44876	0.30735	11.22	<.0001
JUN	1	4.83683	0.29056	16.65	<.0001
JUL	1	5.31469	0.26559	20.01	<.0001
AUG	1	5.33515	0.26352	20.25	<.0001
SEP	1	4.21369	0.27441	15.36	<.0001
OCT	1	2.83854	0.26882	10.56	<.0001
NOV	1	1.06712	0.30227	3.53	0.0006

RAINFALL6 indicates precipitation lagged six months.
LOGSCEGDP6 indicates a log of SCE GDP lagged six months.
Last sample observation was September 2016. First forecast period was October 2016.

Street Light Electricity Use Model

Dependent Variable: STLUSE

Number of Observations Read	105
Number of Observations Used	105

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	1.34477	0.33619	185.53	<.0001
Error	100	0.18121	0.00181		
Corrected Total	104	1.52598			

Root MSE	0.04257	R-Square	0.8812
Dependent Mean	2.89288	Adj R-Sq	0.8765
Coeff Var	1.4715		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-0.0642	0.60028	-0.11	0.915
CUMBDAYS	1	0.00112	0.00011158	10.05	<.0001
RESPRSTRLT	1	0.01035	0.00168	6.17	<.0001
DAYHRS	1	-0.00076539	0.00008786	-8.71	<.0001
LIGHTINDX	1	-0.30076	0.12038	-2.5	0.0141

Last sample observation was September 2016. First forecast period was October 2016.

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.
MAR-AUG	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.
AGRDUMMY1215	Binary variables equal to one from 2012 to 2015 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 to 18 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	177
Number of Observations Used	177

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	13	9751773	750136	3.88	<.0001
Error	163	31475991	193104		
Corrected Total	176	41227764			

Root MSE	439.43627	R-Square	0.2365
Dependent Mean	459.17514	Adj R-Sq	0.1756
Coeff Var	95.70123		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	210.96208	142.56365	1.48	0.1409
LASTRT18	1	0.0124	0.00592	2.09	0.0378
DUMMY_REC0809	1	-450.57828	97.39355	-4.63<.0001	
JAN	1	223.98653	163.31516	1.37	0.1721
FEB	1	481.25431	163.32388	2.95	0.0037
MAR	1	274.10476	163.3278	1.68	0.0952
APR	1	121.02464	163.33262	0.74	0.4598
MAY	1	156.68851	163.35468	0.96	0.3389
JUN	1	-169.16795	163.41883	-1.04	0.3021
JUL	1	9.20395	163.51724	0.06	0.9552
AUG	1	-70.17567	163.57391	-0.43	0.6685
SEP	1	318.59331	163.53245	1.95	0.0531
OCT	1	92.90964	166.13086	0.56	0.5768
NOV	1	104.11183	166.09454	0.63	0.5317

The D_ indicates the first difference.
LASTRT18 denotes Los Angeles County total starts lagged 18 periods.
Last sample observation was September 2016. First forecast period was October 2016.

Residential Electricity Customer Model – Orange County

Dependent Variable: D_orCUS

Number of Observations Read	129
Number of Observations Used	129

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	14	4796190	342585	4.41	<.0001
Error	114	8852422	77653		
Corrected Total	128	13648612			

Root MSE	278.66257	R-Square	0.3514
Dependent Mean	415.17054	Adj R-Sq	0.2718
Coeff Var	67.12002		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	203.32224	100.1883	2.03	0.0447
ORSTRT12	1	0.02898	0.00859	3.37	0.001
DUMMY_201206	1	-1458.72679	292.32468	-4.99	<.0001
DUMMY_201207	1	1290.71647	292.31097	4.42	<.0001
JAN	1	-57.39853	121.77865	-0.47	0.6383
FEB	1	70.13773	121.81439	0.58	0.5659
MAR	1	64.74568	121.8485	0.53	0.5962
APR	1	-12.34009	121.86711	-0.1	0.9195
MAY	1	1.05384	121.86445	0.01	0.9931
JUN	1	74.73344	124.68851	0.6	0.5501
JUL	1	30.46115	124.6952	0.24	0.8074
AUG	1	22.53089	121.78874	0.18	0.8536
SEP	1	113.19553	121.77054	0.93	0.3546
OCT	1	74.91748	124.62534	0.6	0.5489
NOV	1	141.80588	124.62427	1.14	0.2576

The D_ indicates the first difference.
OCSTRT12 denotes Orange County total starts lagged 12 periods.
Last sample observation was September 2016. First forecast period was October 2016.

Residential Electricity Customer Model – Riverside County

Dependent Variable: D_rvCUS

Number of Observations Read	177
Number of Observations Used	177

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	13	72701600	5592431	64.09	<.0001
Error	163	14222674	87256		
Corrected Total	176	86924274			

Root MSE	295.3907	R-Square	0.8364
Dependent Mean	893.54237	Adj R-Sq	0.8233
Coeff Var	33.05839		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	238.2391	84.20216	2.83	0.0053
RVSTRT3	1	0.07219	0.0026	27.79	<.0001
DUMMY_CRASH0708	1	-294.22973	65.07107	-4.52	<.0001
JAN	1	-138.79258	109.77246	-1.26	0.2079
FEB	1	-70.27454	109.77237	-0.64	0.523
MAR	1	-9.40544	109.77245	-0.09	0.9318
APR	1	-211.12574	109.77308	-1.92	0.0562
MAY	1	-161.69519	109.77413	-1.47	0.1427
JUN	1	-138.62968	109.77466	-1.26	0.2084
JUL	1	108.96327	109.77429	0.99	0.3224
AUG	1	-97.51605	109.77339	-0.89	0.3757
SEP	1	4.10869	109.77257	0.04	0.9702
OCT	1	-86.64228	111.65169	-0.78	0.4389
NOV	1	-10.2486	111.64854	-0.09	0.927

The D_ indicates the first difference.
RVSTRT3 denotes Riverside County total starts lagged 3 periods.
Last sample observation was September 2016. First forecast period was October 2016.

Residential Electricity Customer Model – San Bernardino County

Dependent Variable: D_SBCUS

Number of Observations Read	177
Number of Observations Used	177

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	15	28649504	1909967	32.18<.0001	
Error	161	9556835	59359		
Corrected Total	176	38206339			

Root MSE	243.63749	R-Square	0.7499
Dependent Mean	559.84746	Adj R-Sq	0.7266
Coeff Var	43.51855		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	51.06399	69.50433	0.73	0.4636
SBSTRT3	1	0.04444	0.00231	19.28	<.0001
DUMMY_CRASH0708	1	-270.01086	53.74172	-5.02	<.0001
DUMMY_201207	1	1067.06979	252.99628	4.22	<.0001
DUMMY_201206	1	-1239.7867	253.02589	-4.9	<.0001
JAN	1	113.9487	90.54004	1.26	0.21
FEB	1	225.66748	90.53997	2.49	0.0137
MAR	1	183.77968	90.54004	2.03	0.044
APR	1	189.34016	90.54056	2.09	0.0381
MAY	1	100.44756	90.54143	1.11	0.2689
JUN	1	76.11875	92.10505	0.83	0.4098
JUL	1	85.08305	92.10355	0.92	0.357
AUG	1	55.31853	90.54081	0.61	0.5421
SEP	1	146.1514	90.54013	1.61	0.1084
OCT	1	129.11758	92.09007	1.4	0.1628
NOV	1	-33.62934	92.08744	-0.37	0.7154

The D_ indicates the first difference.
SBSTRT3 indicates San Bernardino County starts lagged three periods.
Last sample observation was September 2016. First forecast period was October 2016.

Residential Electricity Customer Model – Ventura/Santa Barbara Counties

Dependent Variable: D_VSBCUS

Number of Observations Read	177
Number of Observations Used	177

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	12	3622739	301895	18.66	<.0001
Error	164	2653804	16182		
Corrected Total	176	6276543			

Root MSE	127.20743	R-Square	0.5772
Dependent Mean	161.59887	Adj R-Sq	0.5462
Coeff Var	78.71802		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	25.7327	36.9301	0.7	0.4869
VSBSTRT	1	0.04774	0.00597	7.99	<.0001
JAN	1	17.80821	47.28114	0.38	0.7069
FEB	1	47.74514	47.27955	1.01	0.3141
MAR	1	2.24511	47.275	0.05	0.9622
APR	1	13.13157	47.27219	0.28	0.7815
MAY	1	-57.97896	47.27184	-1.23	0.2218
JUN	1	-308.1229	47.27299	-6.52	<.0001
JUL	1	122.68186	47.27744	2.59	0.0103
AUG	1	23.09553	47.27981	0.49	0.6259
SEP	1	220.83523	47.27483	4.67	<.0001
OCT	1	89.15728	48.08021	1.85	0.0655
NOV	1	39.20381	48.07992	0.82	0.416

The D_ indicates the first difference.
Last sample observation was September 2016. First forecast period was October 2016.

Residential Electricity Customer Model – Other (Rural) Counties

Dependent Variable: D_OTHCUS

Number of Observations Read	153
Number of Observations Used	153

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	12	2941023	245085	19.83<.0001	
Error	140	1730058	12358		
Corrected Total	152	4671080			

Root MSE	111.16454	R-Square	0.6296
Dependent Mean	199.22222	Adj R-Sq	0.5979
Coeff Var	55.79927		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-77.74002	36.34871	-2.14	0.0342
OTHSTRT	1	0.11904	0.00789	15.08<.0001	
JAN	1	27.17377	44.50238	0.61	0.5424
FEB	1	42.04401	44.50169	0.94	0.3464
MAR	1	17.48675	44.50187	0.39	0.695
APR	1	-2.33324	44.50277	-0.05	0.9583
MAY	1	62.86621	44.50364	1.41	0.16
JUN	1	13.15118	44.50346	0.3	0.768
JUL	1	-16.64942	44.50269	-0.37	0.7089
AUG	1	17.11322	44.50228	0.38	0.7012
SEP	1	62.43207	44.50244	1.4	0.1629
OCT	1	-21.34514	45.38584	-0.47	0.6389
NOV	1	-31.42338	45.38448	-0.69	0.4898

The D_ indicates the first difference.
Last sample observation was September 2016. First forecast period was October 2016.

Commercial Customer Model – Large Customers

Dependent Variable: D_COMLCUS

Number of Observations Read	153
Number of Observations Used	153

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	264601	14700	24.34	<.0001
Error	134	80927	603.93076		
Corrected Total	152	345528			

Root MSE	24.575	R-Square	0.7658
Dependent Mean	7.02614	Adj R-Sq	0.7343
Coeff Var	349.76516		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-23.04381	8.7335	-2.64	0.0093
DSCENFEMP12	1	0.56352	0.12813	4.4	<.0001
DCOMSQFT12	1	0.00697	0.00163	4.28	<.0001
DUMMY_200910	1	-279.26575	26.28738	-10.62	<.0001
DUMMY_200911	1	268.22824	26.60962	10.08	<.0001
DUMMY_201607	1	-108.08036	15.04799	-7.18	<.0001
DUMMY_201608	1	-180.6979	25.72848	-7.02	<.0001
DUMMY_COML	1	144.51397	25.79719	5.6	<.0001
JAN	1	114.54544	27.90503	4.1	<.0001
FEB	1	-10.7752	10.19519	-1.06	0.2925
MAR	1	4.81471	10.06897	0.48	0.6333
APR	1	4.47746	9.92278	0.45	0.6526
MAY	1	17.41824	9.9357	1.75	0.0819
JUN	1	23.30467	10.14216	2.3	0.0231
JUL	1	66.41935	16.62488	4	0.0001
AUG	1	9.07166	10.14296	0.89	0.3727
SEP	1	-3.97144	10.32135	-0.38	0.701
OCT	1	-21.51838	12.06485	-1.78	0.0768
NOV	1	-19.71116	11.02519	-1.79	0.0761

The D_ indicates the first difference.
SCENFEMP12 indicates SCE non-farm employment lagged 12 periods.
COMSQFT12 indicates SCE commercial floor space lagged 12 periods.
Last sample observation was September 2016. First forecast period was October 2016.

Commercial Customer Model – Small Customers

Dependent Variable: D_COMSCUS

Number of Observations Read	177
Number of Observations Used	177

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	14	29394064	2099576	28.26	<.0001
Error	162	12034468	74287		
Corrected Total	176	41428532			

Root MSE	272.55612	R-Square	0.7095
Dependent Mean	638.53672	Adj R-Sq	0.6844
Coeff Var	42.68449		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-33.54964	81.58347	-0.41	0.6814
DCOMSQFT	1	0.17559	0.01874	9.37	<.0001
DSCERESCUS	1	0.11334	0.01441	7.86	<.0001
DUMMY_REC0809	1	-389.68869	70.66062	-5.51	<.0001
JAN	1	-107.73413	101.37301	-1.06	0.2895
FEB	1	-18.76686	101.73778	-0.18	0.8539
MAR	1	64.43191	101.50402	0.63	0.5265
APR	1	113.24512	101.3237	1.12	0.2654
MAY	1	132.85675	101.3238	1.31	0.1916
JUN	1	227.41658	101.96637	2.23	0.0271
JUL	1	-58.78307	101.52054	-0.58	0.5634
AUG	1	20.40149	101.35924	0.2	0.8407
SEP	1	-74.15064	101.87512	-0.73	0.4678
OCT	1	162.90402	103.1472	1.58	0.1162
NOV	1	-51.59738	103.0556	-0.5	0.6173

The D_ indicates the first difference.
Last sample observation was September 2016. First forecast period was October 2016.

Industrial Customer Model

Dependent Variable: D_indCUS

Number of Observations Read	105
Number of Observations Used	105

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	15	122758	8183.86044	10.22	<.0001
Error	89	71272	800.81154		
Corrected Total	104	194030			

Root MSE	28.29861	R-Square	0.6327
Dependent Mean	-32.13333	Adj R-Sq	0.5708
Coeff Var	-88.06623		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-69.8671	13.0802	-5.34	<.0001
DSCEMFGEMP3	1	3.57568	1.20422	2.97	0.0038
DUMMY_200910	1	-163.7946	30.95911	-5.29	<.0001
DUMMY_200911	1	167.35694	30.72637	5.45	<.0001
INDTREND_FLAT	1	0.62312	0.12582	4.95	<.0001
JAN	1	20.85983	14.07771	1.48	0.1419
FEB	1	8.62136	13.84778	0.62	0.5352
MAR	1	28.2187	13.77075	2.05	0.0434
APR	1	-22.97865	17.50753	-1.31	0.1927
MAY	1	10.91462	13.98952	0.78	0.4373
JUN	1	27.53633	13.81029	1.99	0.0492
JUL	1	15.80724	13.75071	1.15	0.2534
AUG	1	10.37915	13.98947	0.74	0.4601
SEP	1	4.01596	14.12415	0.28	0.7768
OCT	1	25.46545	14.67876	1.73	0.0862
NOV	1	6.88776	14.68704	0.47	0.6402

The D_ indicates the first difference.
SCEMFGEMP3 indicates SCE manufacturing employment lagged 3 periods.
Last sample observation was September 2016. First forecast period was October 2016

Other Public Authority Customer Model

Dependent Variable: D_opaCUS

Number of Observations Read	129
Number of Observations Used	129

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	20	20356	1017.7921	5.76	<.0001
Error	108	19084	176.70402		
Corrected Total	128	39440			

Root MSE	13.29301	R-Square	0.5161
Dependent Mean	-31.03101	Adj R-Sq	0.4265
Coeff Var	-42.83782		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-32.88973	4.511	-7.29	<.0001
DSCEGOVEMP12	1	0.36357	0.394	0.92	0.3582
DUMMY_200910	1	-22.44555	14.03746	-1.6	0.1127
DUMMY_200911	1	33.34604	14.0139	2.38	0.0191
DUMMY_201304	1	-50.4936	13.96282	-3.62	0.0005
DUMMY_201305	1	37.90082	14.03134	2.7	0.008
DUMMY_201505	1	-29.8363	14.05894	-2.12	0.0361
DUMMY_201506	1	41.04846	14.04285	2.92	0.0042
DUMMY_201607	1	-73.15116	14.11791	-5.18	<.0001
DUMMY_201608	1	64.91815	14.09019	4.61	<.0001
JAN	1	8.93634	6.55755	1.36	0.1758
FEB	1	3.4085	8.0044	0.43	0.6711
MAR	1	-1.65229	7.98198	-0.21	0.8364
APR	1	3.98423	6.58608	0.6	0.5465
MAY	1	0.78531	7.12884	0.11	0.9125
JUN	1	3.44984	5.98638	0.58	0.5656
JUL	1	20.61875	27.86283	0.74	0.4609
AUG	1	4.31771	5.99548	0.72	0.473
SEP	1	-10.4328	13.63008	-0.77	0.4457
OCT	1	-12.72935	17.15834	-0.74	0.4598
NOV	1	0.70941	8.26267	0.09	0.9317

The D_ indicates the first difference.
Last sample observation was September 2016. First forecast period was October 2016

Agriculture Customer Model

Dependent Variable: D_AGCUS

Number of Observations Read	129
Number of Observations Used	129

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	210615	13163	27.79	<.0001
Error	112	53059	473.73867		
Corrected Total	128	263673			

Root MSE	21.76554	R-Square	0.7988
Dependent Mean	-7.2093	Adj R-Sq	0.77
Coeff Var	-301.90908		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	5.71668	37.03365	0.15	0.8776
DAGEMP24	1	3.74472	5.69746	0.66	0.5124
DUMMY_201304	1	-145.04965	23.53022	-6.16	<.0001
DUMMY_201305	1	65.84932	23.10604	2.85	0.0052
DUMMY_201607	1	-303.6929	22.84657	-13.29	<.0001
DUMMY_201608	1	285.50006	22.83245	12.5	<.0001
JAN	1	-1.7235	22.09111	-0.08	0.938
FEB	1	-7.44957	43.26437	-0.17	0.8636
MAR	1	-28.29477	70.28013	-0.4	0.688
APR	1	-58.68027	133.75726	-0.44	0.6617
MAY	1	-36.68061	99.94953	-0.37	0.7143
JUN	1	-4.74528	33.38886	-0.14	0.8872
JUL	1	41.56188	40.82954	1.02	0.3109
AUG	1	3.7104	12.06884	0.31	0.7591
SEP	1	-19.41676	36.63475	-0.53	0.5972
OCT	1	-28.8747	31.91161	-0.9	0.3675
NOV	1	-11.87481	14.40003	-0.82	0.4113

The D_ indicates the first difference.
AGREMP24 indicates SCE agricultural employment lagged 24 periods.
Last sample observation was September 2016. First forecast period was October 2016.

Street Light Customer Model

Dependent Variable: D_strCUS

Number of Observations Read	105
Number of Observations Used	105

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	15	220017	14668	20.94	<.0001
Error	89	62337	700.41936		
Corrected Total	104	282355			

Root MSE	26.46544	R-Square	0.7792
Dependent Mean	21.37143	Adj R-Sq	0.742
Coeff Var	123.8356		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	34.93554	9.39257	3.72	0.0003
DSCERESCUS18	1	0.01025	0.00183	5.58	<.0001
DUMMY_200811	1	-241.16684	28.43022	-8.48	<.0001
DUMMY_200901	1	102.48194	28.09301	3.65	0.0004
DUMMY_200908	1	-280.06442	28.28299	-9.9	<.0001
JAN	1	-27.38227	13.73875	-1.99	0.0493
FEB	1	-9.71842	13.08315	-0.74	0.4595
MAR	1	-19.32483	13.39515	-1.44	0.1526
APR	1	-16.3194	13.30421	-1.23	0.2232
MAY	1	-29.93635	13.04122	-2.3	0.0241
JUN	1	-26.77544	12.94959	-2.07	0.0416
JUL	1	-36.10229	13.10738	-2.75	0.0071
AUG	1	-65.92423	13.84813	-4.76	<.0001
SEP	1	-36.64732	13.1986	-2.78	0.0067
OCT	1	-28.85038	13.47989	-2.14	0.0351
NOV	1	-46.44839	13.85161	-3.35	0.0012

The D_ indicates the first difference.
SCERESCUS18 indicates SCE residential customers lagged 18 periods.
Last sample observation was September 2016. First forecast period was October 2016.

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
COMSQF	Commercial building total square footage. Compiled from Dodge Data & 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.

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.
L	A symbol after a variable name to denote large commercial class customers (generally those in the TOU rate groups).
S	A symbol after a variable name to denote small commercial class customers (generally those in the GS-1 and GS-2 rate groups).
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
SCEMFGEMP	SCE regional manufacturing employment. Compiled from Moody's Analytics data.
INDCUSDUMMY	Binary variables equal to one on multiple periods, and zero otherwise, that are designed to capture irregularities in customer 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
OPASQF	Government building floor stock. Compiled from Dodge Data & Analytics data.
SCEGOVEMP	SCE regional government employment. Compiled from Moody's Analytics data.
OPACUSDUMMY	Binary variables equal to one on multiple periods, and zero otherwise, that are designed to capture 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

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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.

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Jan-Nov Binary variable set equal to 1 for the designated month and zero otherwise.

11) Model Statistics – Residential Meter Connection Models

The PDLREG Procedure

Ordinary Least Squares Estimates

SSE	20920586.2	DFE	114
MSE	183514	Root MSE	428.38524
SBC	1986.52303	AIC	1943.62585
MAE	321.580356	AICC	1947.87363
MAPE	15.0013473	HQC	1961.05584
Durbin-Watson	1.1374	Total R-Square	0.9227

Parameter Estimates

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	1297	249.7728	5.19	<.0001
JAN	1	-114.1945	187.3457	-0.61	0.5434
FEB	1	-317.5172	187.3172	-1.7	0.0928
MAR	1	39.0732	187.293	0.21	0.8351
APR	1	-246.8355	187.2734	-1.32	0.1901
MAY	1	-62.6458	187.2575	-0.33	0.7386
JUN	1	182.1249	187.2436	0.97	0.3328
JUL	1	-234.6088	187.2308	-1.25	0.2128
AUG	1	131.3387	187.2196	0.7	0.4844
SEP	1	81.6214	187.2116	0.44	0.6637
OCT	1	210.1834	191.591	1.1	0.2749
NOV	1	-28.1829	191.5824	-0.15	0.8833
DUMMY_REC0809	1	141.322	98.1983	1.44	0.1528
SCESTRT**0	1	0.0136	0.000479	28.44	<.0001
SCESTRT**1	1	0	0.		.
SCESTRT**2	1	-0.0052	0	-Infty	<.0001
SCEMULTISHARE**0	1	-526.3167	85.762	-6.14	<.0001
SCEMULTISHARE**1	1	0	0.		.
SCEMULTISHARE**2	1	200.9084	32.7375	6.14	<.0001

Restriction	DF	L Value	Standard Error	t Value	Approx Pr > |t|
SCESTRT(-1)	-1	176142087	83957786	2.1	0.0353
SCESTRT(19)	-1	-1.43E+08	87168970	-1.64	0.1018
SCEMULTISHARE(-1)	-1	-6434	1323	-4.86	<.0001
SCEMULTISHARE(19)	-1	5187	1364	3.8	<.0001

Estimate of Lag Distribution

Variable	Estimate	Standard Error	t Value	Approx Pr > |t|
SCESTRT(0)	0.000848	0.00011	7.72	<.0001
SCESTRT(1)	0.001607	0.00011	14.63	<.0001
SCESTRT(2)	0.002277	0.00011	20.72	<.0001
SCESTRT(3)	0.002857	0.00011	26	<.0001

SCESTRT(4)	0.003348	0.00011	30.47	<.0001
SCESTRT(5)	0.00375	0.00011	34.13	<.0001
SCESTRT(6)	0.004063	0.00011	36.97	<.0001
SCESTRT(7)	0.004286	0.00011	39	<.0001
SCESTRT(8)	0.00442	0.00011	40.22	<.0001
SCESTRT(9)	0.004465	0.00011	40.63	<.0001
SCESTRT(10)	0.00442	0.00011	40.22	<.0001
SCESTRT(11)	0.004286	0.00011	39	<.0001
SCESTRT(12)	0.004063	0.00011	36.97	<.0001
SCESTRT(13)	0.00375	0.00011	34.13	<.0001
SCESTRT(14)	0.003348	0.00011	30.47	<.0001
SCESTRT(15)	0.002857	0.00011	26	<.0001
SCESTRT(16)	0.002277	0.00011	20.72	<.0001
SCESTRT(17)	0.001607	0.00011	14.63	<.0001
SCESTRT(18)	0.000848	0.00011	7.72	<.0001

Estimate of Lag Distribution

Variable	Estimate	Standard Error	t Value	Approx Pr > |t|
SCEMULTISHARE(0)	-32.77373	5.3404	-6.14	<.0001
SCEMULTISHARE(1)	-62.097594	10.1186	-6.14	<.0001
SCEMULTISHARE(2)	-87.971592	14.3347	-6.14	<.0001
SCEMULTISHARE(3)	-110.395723	17.9887	-6.14	<.0001
SCEMULTISHARE(4)	-129.369988	21.0805	-6.14	<.0001
SCEMULTISHARE(5)	-144.894387	23.6102	-6.14	<.0001
SCEMULTISHARE(6)	-156.968919	25.5777	-6.14	<.0001
SCEMULTISHARE(7)	-165.593585	26.9831	-6.14	<.0001
SCEMULTISHARE(8)	-170.768384	27.8263	-6.14	<.0001
SCEMULTISHARE(9)	-172.493318	28.1073	-6.14	<.0001
SCEMULTISHARE(10	-170.768384	27.8263	-6.14	<.0001
SCEMULTISHARE(11	-165.593585	26.9831	-6.14	<.0001
SCEMULTISHARE(12	-156.968919	25.5777	-6.14	<.0001
SCEMULTISHARE(13	-144.894387	23.6102	-6.14	<.0001
SCEMULTISHARE(14	-129.369988	21.0805	-6.14	<.0001
SCEMULTISHARE(15	-110.395723	17.9887	-6.14	<.0001
SCEMULTISHARE(16	-87.971592	14.3347	-6.14	<.0001

SCEMULTISHARE(17	-62.097594	10.1186	-6.14	<.0001
SCEMULTISHARE(18	-32.77373	5.3404	-6.14	<.0001

Last sample observation was September 2016. First forecast period was October 2016.

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.
SCESTRM	Multifamily housing starts as a proportion of total 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.

13) Non Residential Meter Connection Models

Dependent Variable: COM_INDMETER

Number of Observations Read	444
Number of Observations Used	105
Number of Observations with Missing Values	339

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	12	4184472	348706	39.39<.0001	
Error	92	814516	8853.43181		
Corrected Total	104	4998987			

Root MSE	94.09268	R-Square	0.8371
Dependent Mean	538.28571	Adj R-Sq	0.8158
Coeff Var	17.48006		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	230.69782	36.07002	6.4	<.0001
RESMETER24	1	0.12488	0.00582	21.47	<.0001
JAN	1	5.3634	45.73358	0.12	0.9069
FEB	1	-27.97438	45.72108	-0.61	0.5421
MAR	1	9.92595	45.77068	0.22	0.8288
APR	1	2.85669	45.72684	0.06	0.9503
MAY	1	-13.40712	45.74373	-0.29	0.7701
JUN	1	-41.90426	45.77831	-0.92	0.3624
JUL	1	8.70841	45.7216	0.19	0.8494
AUG	1	-54.79575	45.74414	-1.2	0.234
SEP	1	14.01301	45.73009	0.31	0.76
OCT	1	-14.39346	47.09893	-0.31	0.7606
NOV	1	-84.25145	47.05179	-1.79	0.0766

RESMETERS24 indicates residential meters lagged 24 periods
Last sample observation was September 2016. First forecast period was October 2016

Agriculture Meter Connection Model

Dependent Variable: AGMETER

Number of Observations Read	516
Number of Observations Used	177
Number of Observations with Missing Values	339

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	20203	4040.56765	49.95	<.0001
Error	171	13833	80.89311		
Corrected Total	176	34036			

Root MSE	8.99406	R-Square	0.5936
Dependent Mean	30.25424	Adj R-Sq	0.5817
Coeff Var	29.72826		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	10.38778	1.76369	5.89	<.0001
lag1runoff	1	0.00687	0.00426	1.61	0.1082
AGMETER1	1	0.59452	0.05717	10.4	<.0001
DUMMY_201501201609	1	10.00412	2.43063	4.12	<.0001
APR	1	4.64952	2.43784	1.91	0.0582
NOV	1	-5.47956	2.56355	-2.14	0.034

Last sample observation was December 2015. First forecast period was January 2016.

14) Non Residential Meter Connection Models Variable Descriptions

Commercial Meter Connection Model

COMMETER	Recorded number of new non-residential (commercial) meter connections. Source: SCE
COMMETERF	Forecast of new non-residential (commercial) meter connections. Source: SCE
RESMETERF	Residential meter forecast. Source: SCE
SCENFEMP	SCE regional non-farm employment. Compiled from Moody's Analytics data.
COMTREND	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.

Agriculture Meter Connection Model

AGMETER	Recorded number of new agricultural meter connections. Source: SCE
AGMETERF	Forecast of new agricultural meter connections. Source: SCE
RUNOFF(-1)	Full natural flow of the San Joaquin River at Friant Dam in cubic feet of flow per second lagged one period. Sources: U.S. Department of the Interior and SCE
AGMETER(-1)	Recorded number of new of new agricultural meter connections lagged one period. 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.
APR	Binary variables set equal to 1 for the month of April and zero otherwise.
NOV	Binary variables set equal to 1 for the month of November and zero otherwise.