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SCE 2015 IEPR Sales and Customer Forecast Work Papers

Form 4 Demand Forecast Methods and Models

Southern California Edison

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1) Introduction

SCE uses econometric models to forecast monthly retail electricity sales (billed recorded sales measured at the customer meter) by customer class. Retail sales are final sales to both bundled and direct access customers within the SCE service territory. 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, other public authority, agriculture and street lighting. Each customer class forecast is itself the product of two separate forecasts: a forecast of electricity consumption per customer or building square foot and a forecast of the number of customers or total building square feet. 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 forecast according to geographical region. The SCE service area encompasses several distinct building climate zones. Accordingly, we model residential electricity consumption in part to capture regional variation in the weather/consumption relationship. Additionally, the commercial customer class is now modeled and forecast according to a small and large customer criteria. Small customers are generally those in the GS-1 and GS-2 rate categories while large customers are typically TOU rate class customers. We find that small and large commercial customers have different electricity use responses to changes in weather, rates and economic conditions.

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 and demographic 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.

As indicated, retail sales include sales to both bundled and Direct Access (DA) customers. DA sales are subtracted from the retail sales forecast in order to derive to the forecast of SCE bundled customer sales.

Partial Direct Access Reopening

Already closed as end of 2013. Therefore SCE has incorporated all the migrating load through the partial DA reopening period through the end of 2013. 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

SCE uses employment per customer or per square foot in most residential models to explain how electricity consumption varies in response to changing economic conditions. It turns out that changes in employment are often an important source of explanatory power in measuring and predicting variation in electricity consumption. The assumption is that an increase in the number employed per customer or per square foot (energy intensity) increases electricity use because an increase in employment is associated with an increase in energy using office and factory machines and equipment (electricity and labor are complimentary inputs). Changes in employment per customer or per square foot cause both seasonal variations in electricity consumption and changes in the long term trend rate of growth in consumption over the forecast period.

When appropriate, SCE matches employment on a sectoral basis with electricity consumption by customer class. Specifically, private commercial services employment in counties served by SCE is assumed to explain changes in SCE small commercial class electricity sales, Manufacturing employment contributes to the explanation of changes in industrial class electricity sales, government employment (federal, state and local) is used to model Public Authority customer class electricity sales and finally agriculture employment is used to help explain changes in Agriculture customer class sales. Employment is expressed on a per customer basis in the Commercial and Agriculture class models and on a square foot basis in the Industrial and Public Authority customer classes.

Historical and forecast employment data by county is obtained from the California Economic Development Department. Moody’s Analytics (MS) provides forecast employment data. MA obtains state and MSA-level historical employment data from the Bureau of Labor Statistics, who coordinates collection and publishing of sub-national level data with state employment agencies including the California Employment Development Department (CA EDD). In the case of Riverside and San Bernardino counties, which are grouped into a single metro area,employment forecast was divided using historical county population figures obtained from the CA EDD.

The employment elasticity in the commercial customer class model is in the range of 0.1 to 0.4. The manufacturing employment elasticity is 0.4. The short-run government employment elasticity is estimated to be about 0.4 and the agriculture employment elasticity is quite small.

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 and heating degree days. 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. We define the cooling degree day (summer) season as April to October and the heating degree day (winter) season as November to March. 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 Pomona, Palm Springs, Long Beach, Riverside, San Gabriel, 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 stations weights reflect the changing geographical customer distribution. SCE customers are 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.

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In the Residential models, the stations selected represent temperatures in the counties served by SCE. For example, the Residential L.A. county model uses a customer weighted average of temperatures recorded by the LAX, Long Beach and San Gabriel weather stations. The commercial sales models are estimated with customer and appliance weighted CDDs/HDDs. The 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 trend growth. 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. We attempt to simplify these issues by sometimes using an average unit revenue price with a one period lag. (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 elasticity, as derived from our forecast models, is generally in the range of -0.08 to -0.2. 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.

Electricity Conservation Programs

SCE no longer takes the position that energy efficiency (EE) should be explicitly included in the econometric estimation of kWh consumption per customer. Instead, EE is omitted from econometric estimations and is deducted after the fact on an incremental basis as needed..

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 contraction and recovery, 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. 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 0.2 to 0.6. We use historical and forecast real income 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 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 bypass co-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 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.

There are approximately 103,500 operational solar systems ranging in size from 1KW to 1030 KW within the SCE service area. The forecast for 2014 includes solar facilities currently in the pipeline. The projection of solar bypass for 2014 includes solar facilities currently in the pipeline and targets set in the California Solar Initiative (CSI) and the 2014 through 2016 is based on the target set in the California Solar Initiative.

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.

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 daily hours of sunlight. The hourly loads are summed by month in order to produce a solar by-pass consumption variable for use in the econometric models. The monthly thermal and solar by-pass variables are summed for a single by-pass variable suitable for inclusion in the sales forecasting models.

Other EX Post Modifications to the Forecast

SCE makes a number of 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, …,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 = $\text{SQRT}(\sum_{t=T+1} (S_{F,t} - S_{N,t})^2 / h)$

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

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 October 2011 forecast compared to actual weather adjusted monthly sales for the period January 2012 to December 2012 reveals the following:

SCE Sales Forecast Evaluation for 2014

Month	Actual (Weather Adj.) MWh	Forecast April 2013 Vintage MWh	MAPE Calculation
Jan-14	7,059,652	7,153,708	0.0132

Feb-14	5,934,474	6,104,805	0.0283
Mar-14	6,206,111	6,796,658	0.0908
Apr-14	6,742,191	6,006,743	0.1154
May-14	6,808,854	6,442,994	0.0552
Jun-14	7,444,740	7,174,650	0.0369
Jul-14	8,524,007	7,633,726	0.1102
Aug-14	8,373,488	8,249,038	0.0150
Sep-14	8,788,627	7,963,338	0.0985
Oct-14	8,305,567	7,359,456	0.1208
Nov-14	5,914,663	6,726,891	0.1285
Dec-14	7,316,042	7,086,260	0.0319
Jan-Aug Total (GWh)	57,094	55,562	5.8%
Jan-Dec Total (GWh)	87,418	84,698	7.0%
Simple Error - Jan-Aug	-2.7%		
Simple Error - Jan-Dec	-3.1%		
MAPE Error: Jan-Aug	5.8%		
MAPE Error: Jan-Dec	7.0%		

The analysis shows that the April 2013 SCE billed month retail sales under-portrayed actual weather adjusted retail sales. Up to August, the forecast Mean Absolute Error (MAPE) was just 5.8 percent. But for the year in total, the MAPE was 7.0 percent due in large part to a sharp increase in cooling degree days of 17% from 2013.

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 weather stations used in the model include Pomona-Ontario, Palm Springs, Long Beach, Riverside, San Gabriel, Santa Ana, Oxnard, Fresno, Lancaster and Los Angeles International Airport. The maximum and minimum temperature for each station is recorded for use in the WMS.

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 contiguous 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 decomposed into the 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 are calculated using 65 degrees while CDD are calculated using 70 degrees. Using 70 degrees for calculating CDD more closely approximates the temperature at which air conditioning is a factor.

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 (1974 to 2003) 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:

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

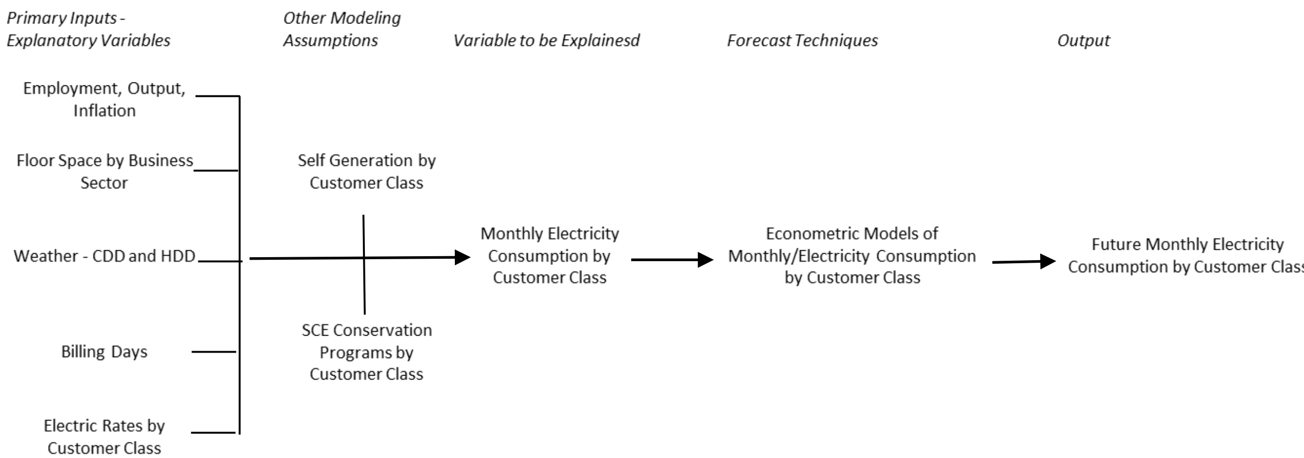
where S is the standard error of regression. These standard errors account for both innovation uncertainty (the first term) and coefficient uncertainty (the second term). Point forecasts made from linear regression models estimated by least squares are optimal in the sense that they have the smallest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

Exogenous Variable Uncertainty

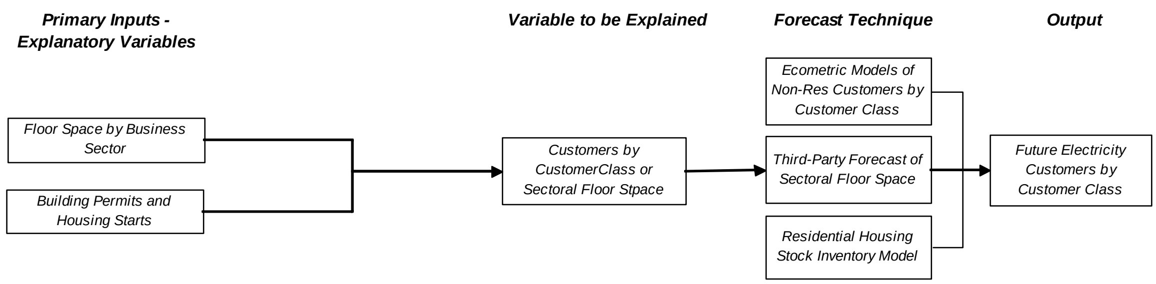
Exogenous variable uncertainty, i.e., uncertainty regarding future weather conditions, economic conditions, etc., is handled through the construction of forecast scenarios. For example, we typically include along with a base case forecast, alternative high and low economic case forecasts. Economic High and Low case assumptions are available from Moody's Analytics.

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

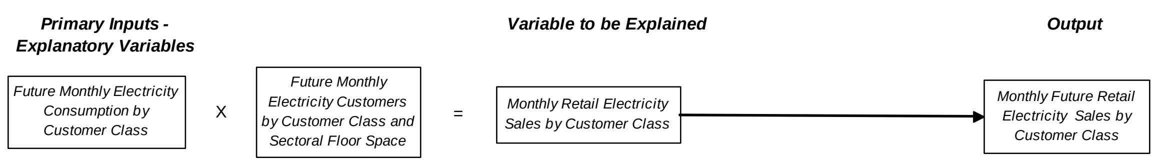
Electricity Consumption (kWh per Customer) Modeling and Forecasting



Electric Customer Modeling and Forecasting



Electric Retail Sales Modeling and Forecasting



Note: Customer Classes = Residential, Commercial, Industrial, Other Public Authority, Agriculture, Street Lighting.

7) Model Statistics – Electricity Use Models

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

Residential Electricity Use Model – L.A. County

Dependent Variable: LAUSE
Method: Least Squares
Sample: 2002M01 2014M03
Included observations: 147

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-1,497.5160	176.9340	-8.4637	0.0000
(LACDD)*SUMSEAS*LASIZE	0.0006	0.0000	16.7515	0.0000
(LAHDD)*WINSEAS*LASIZE	0.0002	0.0000	7.3268	0.0000
CUMBDAYS	0.7448	0.0522	14.2659	0.0000
LOG(LAREALGDP)	252.6453	28.4589	8.8776	0.0000
RESRATE	-6.2362	1.9317	-3.2283	0.0016
JAN	11.8071	6.5986	1.7893	0.0759
FEB	-17.5637	8.2948	-2.1174	0.0361
MAR	-20.6456	6.1286	-3.3687	0.0010
APR	-32.2746	7.3097	-4.4153	0.0000
MAY	-8.3886	11.0515	-0.7591	0.4492
JUN	4.1137	11.1028	0.3705	0.7116
JUL	29.7124	12.7252	2.3349	0.0211
AUG	47.3149	13.6896	3.4563	0.0007
SEP	26.4327	14.2276	1.8579	0.0655
OCT	7.0318	11.7124	0.6004	0.5493
NOV	-1.8312	8.8623	-0.2066	0.8366

R-squared	0.9650	Mean dependent var	519.6024
Adjusted R-squared	0.9607	S.D. dependent var	76.0752
S.E. of regression	15.0738	Akaike info criterion	8.3722
F-statistic	224.2965	Durbin-Watson stat	1.3214
Prob(F-statistic)	0.0000		

Residential Electricity Use Model – Orange County

Dependent Variable: ORUSE
Method: Least Squares
Sample: 2002M01 2014M03
Included observations: 147

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-625.8037	147.9053	-4.2311	0.0000
(ORCDD)*SUMSEAS*ORSIZE	0.0006	0.0001	12.9749	0.0000
(ORHDD)*WINSEAS*ORSIZE	0.0002	0.0000	3.7914	0.0002
CUMBDAYS	0.9296	0.0699	13.2899	0.0000
LOG(ORREALGDP)	118.1007	26.8075	4.4055	0.0000
RESRATE	-4.2827	2.5575	-1.6746	0.0964
JAN	9.1278	9.2970	0.9818	0.3280
FEB	-22.2638	11.4155	-1.9503	0.0533
MAR	-36.2731	8.2087	-4.4188	0.0000
APR	-48.6338	9.0131	-5.3959	0.0000
MAY	-30.4984	13.1512	-2.3191	0.0220
JUN	-16.1971	12.9826	-1.2476	0.2144
JUL	23.6863	13.4696	1.7585	0.0810
AUG	49.2094	14.2778	3.4466	0.0008
SEP	31.7791	15.2446	2.0846	0.0391
OCT	-1.3007	13.6640	-0.0952	0.9243
NOV	-11.7033	11.5522	-1.0131	0.3129

R-squared	0.9311	Mean dependent var	556.4766
Adjusted R-squared	0.9226	S.D. dependent var	72.4940
S.E. of regression	20.1649	Akaike info criterion	8.9542
F-statistic	109.8102	Durbin-Watson stat	0.9141
Prob(F-statistic)	0.0000		

Residential Electricity Use Model – Riverside County

Dependent Variable: RVUSE
Method: Least Squares
Sample: 2002M01 2014M03
Included observations: 147

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-761.7465	146.4605	-5.2010	0.0000
(RIVCDD)*SUMSEAS*RVSIZE	0.0008	0.0000	16.7200	0.0000
(RIVHDD)*WINSEAS*RVSIZE	0.0001	0.0000	1.4092	0.1612
CUMBDAYS	1.0747	0.1041	10.3231	0.0000
LOG(RVREALGDP)	240.3338	34.2459	7.0179	0.0000
RESRATE	-6.2128	3.8654	-1.6073	0.1104
JAN	31.8048	13.4691	2.3613	0.0197
FEB	8.6331	16.5721	0.5209	0.6033
MAR	-18.0908	12.4015	-1.4588	0.1471
APR	-24.9085	15.5293	-1.6040	0.1112
MAY	-47.1706	21.8448	-2.1594	0.0327
JUN	-21.3932	23.4930	-0.9106	0.3642
JUL	40.3188	31.5060	1.2797	0.2029
AUG	104.4351	34.6755	3.0118	0.0031
SEP	41.4630	34.8407	1.1901	0.2362
OCT	-15.4160	25.1698	-0.6125	0.5413
NOV	21.7923	18.3786	1.1857	0.2379
CAC	-163.6734	31.3771	-5.2163	0.0000

R-squared	0.9827	Mean dependent var	747.1910
Adjusted R-squared	0.9804	S.D. dependent var	215.9847
S.E. of regression	30.2325	Akaike info criterion	9.7700
F-statistic	430.7437	Durbin-Watson stat	1.5746
Prob(F-statistic)	0.0000		

Residential Electricity Use Model – San Bernardino County

Dependent Variable: SBERDUSE
Method: Least Squares
Sample: 2002M01 2014M03
Included observations: 147

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-946.7712	118.1350	-8.0143	0.0000
(SBERDCDD)*SUMSEAS*SBERDSIZE	0.0007	0.0000	20.8941	0.0000
(SBERDHDD)*WINSEAS*SBERDSIZE	0.0001	0.0000	4.4206	0.0000
CUMBDAYS	0.9415	0.0688	13.6822	0.0000
LOG(SBERDREALGDP)	241.2525	27.7689	8.6879	0.0000
RESRATE	-7.7831	2.5452	-3.0579	0.0027
JAN	9.6984	8.9157	1.0878	0.2787
FEB	-9.8311	10.9635	-0.8967	0.3715
MAR	-19.6090	8.1931	-2.3934	0.0181
APR	-31.5578	10.3428	-3.0512	0.0028
MAY	-17.7893	15.7912	-1.1265	0.2620
JUN	5.8020	16.1515	0.3592	0.7200
JUL	46.4395	20.0402	2.3173	0.0221
AUG	87.1417	21.8364	3.9907	0.0001
SEP	47.8944	21.9597	2.1810	0.0310
OCT	9.7228	17.0545	0.5701	0.5696
NOV	8.9270	12.3774	0.7212	0.4721
CAC	-37.7094	20.4563	-1.8434	0.0676

R-squared	0.9851	Mean dependent var	619.4828
Adjusted R-squared	0.9831	S.D. dependent var	153.6904
S.E. of regression	19.9587	Akaike info criterion	8.9395
F-statistic	501.6631	Durbin-Watson stat	1.7166
Prob(F-statistic)	0.0000		

Residential Electricity Use Model – Ventura/Santa Barbara Counties

Dependent Variable: VENUSE
Method: Least Squares
Sample: 2002M01 2014M03
Included observations: 147

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-1,171.0820	117.8615	-9.9361	0.0000
(VENCDD)*SUMSEAS*VENSIZE	0.0004	0.0000	13.1630	0.0000
(VENHDD)*WINSEAS*VENSIZE	0.0002	0.0000	7.1095	0.0000
CUMBDAYS	0.8057	0.0466	17.3046	0.0000
LOG(VENREALGDP)	360.2138	33.3099	10.8140	0.0000
RESRATE	-2.9370	1.7143	-1.7132	0.0891
JAN	11.7287	5.7548	2.0381	0.0436
FEB	-25.8898	7.3845	-3.5060	0.0006
MAR	-29.8523	5.4312	-5.4965	0.0000
APR	-49.1334	6.1327	-8.0117	0.0000
MAY	-32.0214	9.4496	-3.3886	0.0009
JUN	-22.9941	9.4120	-2.4431	0.0159
JUL	-16.6207	10.3832	-1.6007	0.1119
AUG	-3.8665	11.0709	-0.3492	0.7275
SEP	-20.7103	11.8064	-1.7542	0.0818
OCT	-18.9809	9.9977	-1.8985	0.0599
NOV	-17.3332	7.5484	-2.2963	0.0233
CAC	-155.1341	20.5580	-7.5462	0.0000

R-squared	0.9510	Mean dependent var	559.0936
Adjusted R-squared	0.9446	S.D. dependent var	57.0593
S.E. of regression	13.4334	Akaike info criterion	8.1476
F-statistic	147.3598	Durbin-Watson stat	1.3941
Prob(F-statistic)	0.0000		

Residential Electricity Use Model – Other (Rural) Counties

Dependent Variable: OTHUSE
Method: Least Squares
Sample: 2002M01 2014M03
Included observations: 147

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-456.2812	95.0298	-4.8015	0.0000
(OTHCDD)*SUMSEAS*OTHSIZE	0.0006	0.0000	16.1706	0.0000
(OTHHDD)*WINSEAS*OTHSIZE	0.0001	0.0000	3.8386	0.0002
CUMBDAYS	0.9159	0.0715	12.8132	0.0000
LOG(OTHREALGDP)	178.7522	29.8018	5.9980	0.0000
RESRATE	-8.6367	2.6978	-3.2013	0.0017
JAN	33.4077	9.7488	3.4268	0.0008
FEB	2.4369	11.2901	0.2158	0.8294
MAR	-13.1633	9.7527	-1.3497	0.1795
APR	-29.5885	13.8919	-2.1299	0.0351
MAY	-17.3168	21.4062	-0.8090	0.4200
JUN	20.2889	22.8685	0.8872	0.3766
JUL	51.3733	29.5920	1.7361	0.0849
AUG	78.7169	31.0839	2.5324	0.0125
SEP	31.3418	28.1335	1.1140	0.2673
OCT	6.7260	22.1965	0.3030	0.7624
NOV	-16.3927	14.9755	-1.0946	0.2757
REALTREND	-0.0238	0.0490	-0.4857	0.6280

R-squared	0.9852	Mean dependent var	650.7566
Adjusted R-squared	0.9833	S.D. dependent var	160.4059
S.E. of regression	20.7415	Akaike info criterion	9.0164
F-statistic	506.0604	Durbin-Watson stat	1.5083
Prob(F-statistic)	0.0000		

The symbol (-1) indicates that the variable is lagged 1 period.

Commercial Electricity Use Model – Large Customers

Dependent Variable: COMLUSE
Method: Least Squares
Sample (adjusted): 2002M02 2014M03
Included observations: 144 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-346.7617	52.5795	-6.5950	0.0000
COMCDD*SUMSEAS	0.0287	0.0116	2.4838	0.0143
CUMBDAYS	0.1515	0.0116	13.1009	0.0000
COMLRATE(-12)	-0.1282	0.3515	-0.3646	0.7160
LOG(REALGDP)	58.5992	7.4921	7.8214	0.0000
JAN	-6.5983	1.4026	-4.7043	0.0000
FEB	0.8173	1.8337	0.4457	0.6566
MAR	-0.7673	1.3538	-0.5667	0.5719
APR	0.0400	1.4587	0.0274	0.9782
MAY	4.3746	1.5075	2.9019	0.0044
JUN	8.1352	1.5160	5.3662	0.0000
JUL	9.1941	2.1731	4.2309	0.0000
AUG	16.3522	2.5027	6.5338	0.0000
SEP	8.8563	2.6458	3.3473	0.0011
OCT	11.3902	1.7802	6.3982	0.0000
NOV	4.6215	1.6192	2.8541	0.0050
CAC	-21.8429	4.9223	-4.4375	0.0000
R-squared	0.9077	Mean dependent var		119.9949
Adjusted R-squared	0.8961	S.D. dependent var		10.4161
S.E. of regression	3.3581	Akaike info criterion		5.3711
Sum squared resid	1,432.1390	Schwarz criterion		5.7217
Log likelihood	-369.7191	Hannan-Quinn criter.		5.5136
F-statistic	78.0516	Durbin-Watson stat		2.2520
Prob(F-statistic)	0.0000			

R-squared	0.9077	Mean dependent var	119.9949
Adjusted R-squared	0.8961	S.D. dependent var	10.4161
S.E. of regression	3.3581	Akaike info criterion	5.3711
F-statistic	78.0516	Durbin-Watson stat	2.2520
Prob(F-statistic)	0.0000		

The symbol (#) indicates that the variable is lagged # periods.

Commercial Electricity Use Model – Small Customers

Dependent Variable: COMSUSE
Method: Least Squares
Sample (adjusted): 2002M02 2014M03
Included observations: 144 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-10.9696	2.9793	-3.6819	0.0003
((COMCDD*COMSIZE))*SUMSEAS	0.0000	0.0000	7.3455	0.0000
CUMBDAYS	0.0062	0.0003	20.4434	0.0000
LOG(COMEMPLOY)	1.6760	0.3063	5.4724	0.0000
COMSRATE(-9)	-0.0066	0.0092	-0.7195	0.4732
DAYHRS*COMSIZE	0.0000	0.0000	-1.0928	0.2766
CAC	-2.0118	0.1182	-17.0182	0.0000
JAN	-0.1228	0.0365	-3.3612	0.0010
FEB	0.0732	0.0479	1.5290	0.1288
MAR	0.0877	0.0680	1.2896	0.1995
APR	0.1511	0.1069	1.4135	0.1600
MAY	0.2751	0.1502	1.8312	0.0694
JUN	0.4918	0.2012	2.4443	0.0159
JUL	0.5689	0.2143	2.6543	0.0090
AUG	0.7218	0.1679	4.2998	0.0000
SEP	0.5326	0.1474	3.6142	0.0004
OCT	0.4623	0.0962	4.8080	0.0000
NOV	0.2144	0.0537	3.9912	0.0001
R-squared	0.9669	Mean dependent var		4.2222
Adjusted R-squared	0.9625	S.D. dependent var		0.4518
S.E. of regression	0.0875	Akaike info criterion		-1.9178
Sum squared resid	0.9648	Schwarz criterion		-1.5465
Log likelihood	156.0792	Hannan-Quinn criter.		-1.7669
F-statistic	216.7828	Durbin-Watson stat		2.3437
Prob(F-statistic)	0.0000			

R-squared	0.9669	Mean dependent var	4.2222
Adjusted R-squared	0.9625	S.D. dependent var	0.4518
S.E. of regression	0.0875	Akaike info criterion	-1.9178
F-statistic	216.7828	Durbin-Watson stat	2.3437
Prob(F-statistic)	0.0000		

The symbol (#) indicates that the variable is lagged # periods.

Industrial Electricity Use Model

Dependent Variable: INDUSE
Method: Least Squares
Sample (adjusted): 2002M02 2014M03
Included observations: 144 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-11.4269	1.5720	-7.2691	0.0000
(COMCDD)*SUMSEAS	-0.0001	0.0003	-0.3795	0.7050
CUMBDAYS	0.0022	0.0003	6.4580	0.0000
INDRATE	-0.0143	0.0115	-1.2423	0.2164
LOG(MFGEMP_BASE)	1.9142	0.2265	8.4523	0.0000
JAN	-0.0642	0.0405	-1.5845	0.1156
FEB	0.0500	0.0530	0.9436	0.3472
MAR	0.0356	0.0391	0.9096	0.3648
APR	0.0907	0.0422	2.1522	0.0333
MAY	0.1323	0.0436	3.0364	0.0029
JUN	0.2180	0.0438	4.9740	0.0000
JUL	0.2111	0.0630	3.3521	0.0011
AUG	0.3863	0.0726	5.3210	0.0000
SEP	0.1809	0.0768	2.3557	0.0200
OCT	0.2053	0.0516	3.9815	0.0001
NOV	0.1102	0.0468	2.3550	0.0201
REALTREND	0.0009	0.0007	1.3051	0.1942
R-squared	0.8548	Mean dependent var		2.7138
Adjusted R-squared	0.8365	S.D. dependent var		0.2400
S.E. of regression	0.0970	Akaike info criterion		-1.7168
Sum squared resid	1.1961	Schwarz criterion		-1.3662
Log likelihood	140.6076	Hannan-Quinn criter.		-1.5743
F-statistic	46.7306	Durbin-Watson stat		1.3649
Prob(F-statistic)	0.0000			

R-squared	0.8548	Mean dependent var	2.7138
Adjusted R-squared	0.8365	S.D. dependent var	0.2400
S.E. of regression	0.0970	Akaike info criterion	-1.7168
F-statistic	46.7306	Durbin-Watson stat	1.3649
Prob(F-statistic)	0.0000		

Other Public Authority Electricity Use Model

Dependent Variable: OPAUSE
Method: Least Squares
Sample (adjusted): 2002M02 2014M03
Included observations: 144 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-2.1887	2.1721	-1.0076	0.3155
COMCDD	0.0005	0.0002	2.4652	0.0150
CAC	-2.4759	0.1088	-22.7557	0.0000
OPARATE(-12)	-0.0091	0.0076	-1.1964	0.2337
LOG(GOVEMP_BASE)	0.6852	0.3054	2.2440	0.0265
CUMBDAYS	0.0015	0.0002	9.1591	0.0000
DAYHRS/LIGHTINDX	0.0042	0.0005	7.6985	0.0000
MAR	-0.1568	0.0269	-5.8379	0.0000
APR	-0.2420	0.0353	-6.8594	0.0000
MAY	-0.2800	0.0440	-6.3601	0.0000
JUN	-0.2750	0.0557	-4.9399	0.0000
JUL	-0.3344	0.0448	-7.4695	0.0000
AUG	-0.1177	0.0301	-3.9096	0.0001
R-squared	0.9477	Mean dependent var		1.6149
Adjusted R-squared	0.9429	S.D. dependent var		0.2992
S.E. of regression	0.0715	Akaike info criterion		-2.3521
Sum squared resid	0.6698	Schwarz criterion		-2.0840
Log likelihood	182.3522	Hannan-Quinn criter.		-2.2432
F-statistic	197.6505	Durbin-Watson stat		1.8454
Prob(F-statistic)	0.0000			

R-squared	0.9477	Mean dependent var	1.6149
Adjusted R-squared	0.9429	S.D. dependent var	0.2992
S.E. of regression	0.0715	Akaike info criterion	-2.3521
F-statistic	197.6505	Durbin-Watson stat	1.8454
Prob(F-statistic)	0.0000		

The symbol (#) indicates that the variable is lagged # periods.

Agriculture Electricity Use Model

Dependent Variable: AGUSE
Method: Least Squares
Sample: 2002M01 2014M03
Included observations: 147

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-64.6311	6.9815	-9.2574	0.0000
CUMBDAYS	0.0078	0.0026	3.0268	0.0030
FPRECIP(-1)	-0.2804	0.0788	-3.5590	0.0005
LOG(REALGDP(-8))	9.4124	1.0029	9.3854	0.0000
JAN	0.1251	0.3161	0.3959	0.6929
FEB	0.4481	0.4022	1.1140	0.2673
MAR	0.8876	0.3069	2.8921	0.0045
APR	2.2044	0.3383	6.5162	0.0000
MAY	3.4292	0.3883	8.8306	0.0000
JUN	4.2191	0.3636	11.6041	0.0000
JUL	4.4359	0.3234	13.7157	0.0000
AUG	4.4676	0.3144	14.2104	0.0000
SEP	3.3026	0.3328	9.9233	0.0000
OCT	2.1287	0.3287	6.4770	0.0000
NOV	0.7215	0.3596	2.0064	0.0469
RUNOFF	-0.0031	0.0006	-5.5491	0.0000
R-squared	0.8795	Mean dependent var		5.0648
Adjusted R-squared	0.8658	S.D. dependent var		2.0293
S.E. of regression	0.7435	Akaike info criterion		2.3476
Sum squared resid	72.4171	Schwarz criterion		2.6731
Log likelihood	-156.5467	Hannan-Quinn criter.		2.4798
F-statistic	63.7717	Durbin-Watson stat		0.4807
Prob(F-statistic)	0.0000			
Prob(F-statistic)	0.0000			

The symbol (-#) indicates that the variable is lagged # period.

R-squared	0.8795	Mean dependent var	5.0648
Adjusted R-squared	0.8658	S.D. dependent var	2.0293
S.E. of regression	0.7435	Akaike info criterion	2.3476
F-statistic	63.7717	Durbin-Watson stat	0.4807
Prob(F-statistic)	0.0000		

Street Light Electricity Use Model

Dependent Variable: STRLTUSE
Method: Least Squares
Sample: 2002M01 2014M03
Included observations: 147

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
Intercept	4.2233	0.7745	5.4527	0.0000
CUMBDAYS	0.0010	0.0001	10.2473	0.0000
RESPRSTRLT	0.0062	0.0003	18.6809	0.0000
NIGHTHRS	0.0008	0.0001	10.7745	0.0000
LIGHTINDX	-3.9233	0.6843	-5.7334	0.0000
R-squared	0.9399	Mean dependent var		3.0925
Adjusted R-squared	0.9382	S.D. dependent var		0.1897
S.E. of regression	0.0472	Akaike info criterion		-3.2368
Sum squared resid	0.3159	Schwarz criterion		-3.1351
Log likelihood	242.9043	Hannan-Quinn criter.		-3.1955
F-statistic	554.9965	Durbin-Watson stat		1.8552
Prob(F-statistic)	0.0000			

R-squared	0.9399	Mean dependent var	3.0925
Adjusted R-squared	0.9382	S.D. dependent var	0.1897
S.E. of regression	0.0472	Akaike info criterion	-3.2368
F-statistic	554.9965	Durbin-Watson stat	1.8552
Prob(F-statistic)	0.0000		

8) Electricity Use Model Variable Description

Residential Electricity Use Model

Use	Recorded residential class monthly electricity consumption in kWh per customer. Source: SCE.
CDD	Cooling degree-days. Source: SCE and National Weather Service.
HDD	Heating degree-days. Source: SCE and National Weather Service.
ResRate	Residential constant $2000 dollar price of electricity in cents per kWh. Source: SCE and Global Insight.
RealGDP	Constant $2005 dollar gross metro product. Sources: Moody's Analytics.
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.
Size	Average residential household size in square feet. Source: McGraw-Hill.
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.
LA	Prefix in front of variable name to denote Los Angeles County.
OR	Prefix in front of variable name to denote Orange County.
SBerd	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	Combined recorded commercial class monthly electricity and direct generation consumption in MWh per commercial customer. Source: SCE.
ComCDD	Cooling degree-days, dynamic population share weighted. Source: SCE and National Weather Service
ComRate	Commercial class constant dollar price of electricity in cents per kWh. Source: SCE and Global Insight
ComSize	Average commercial building size in square feet. Source: McGraw-Hill 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 April to October and zero otherwise.
CAC	An index measuring the average efficiency of central air conditioning equipment. Source: Energy Information Administration.
S	A symbol after a variable name to denote small commercial class customers (generally those in the GS-1 and GS-2 rate groups).
L	A symbol after a variable name to denote large commercial class customers (generally those in the TOU rate groups).

Industrial Electricity Use Model

IndUse	Combined recorded industrial class monthly electricity consumption and direct generation in kWh per industrial building square feet. Source: SCE and McGraw-Hill.
CDD	Cooling degree-days static population weighting. Source: SCE and National Weather Service.
IndRate	Industrial class constant $2000 dollar price of electricity in cents per kWh. Source: SCE and Global Insight.
MfgEmp	Manufacturing sector monthly employment per industrial building thousand square feet. Source: Global Insight and McGraw-Hill.
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 April to October and zero otherwise.
CAC	An index measuring the average efficiency of central air conditioning equipment. Source: Energy Information Administration.
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 and direct generation in kWh per government building square feet. Source: SCE and McGraw-Hill.
ComCDD	Cooling degree-days, static population weighted. Source: SCE and National Weather Service
OPARate	Other Public Authority class constant $2000 dollar price of electricity in cents per kWh. Source: SCE and Global Insight
TotEmp	Total non-farm employment Source: Moody's Analytics.
CumBDays	Average number of days in monthly billing statement multiplied by the number of billing cycles in month. Source: SCE
DayHrs	Number of hours of daylight in a month in S. California (a proxy for office lighting use).
LightIndx	An index of commercial building lighting efficiency, Source: Energy Information Administration.
Mar-Aug	Binary variable set equal to 1 for the designated month and zero otherwise.
CAC	An index measuring the average efficiency of central air conditioning equipment. Source: Energy Information Administration.

Agriculture Electricity Use Model

AgUse	Recorded agriculture class monthly electricity consumption in MWh per agriculture customer. Source: SCE.
RealGDP	Constant $2005 dollar gross metro product. Sources: Moody's Analytics.
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. Source: U.S Department of the Interior.
Precip	Fresno monthly precipitation level in inches. Source: NOAA.
Jan-Nov	Binary variable set equal to 1 for the designated month and zero otherwise.
Dummy	Binary variables equal to one or zero that are designed to capture billing irregularities in customer data.

Street Lighting Electricity Use Model

StLtUse	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.
NightHrs	Number of hours of between sunset and sunrise in a month in S. California.
LightIndx	An index of commercial building lighting efficiency, Source: Energy Information Administration.

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 in Section 10. The Residential customer models are constructed on the basis that new customers are determined mainly by employment and population (with a lag extending a year or longer months depending upon the region). The employment and population forecasts are from from Moody's Analytics.

Note that in the case of the industrial and Other Public Authority 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 McGraw-Hill.

Residential Customers

Residential Electricity Customer Model – L.A. County

Dependent Variable: D(LACUST1)
Method: Least Squares
Sample: 2002Q1 2014Q1
Included observations: 49

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	0.9173	0.1056	8.6849	0.0000
D(LAET_V2)	0.0063	0.0033	1.9030	0.0634
D(LAPOP(-11))	0.0440	0.0075	5.9033	0.0000
LADUMMY	1.0951	0.3196	3.4268	0.0013
R-squared	0.6064	Mean dependent var		1.4219
Adjusted R-squared	0.5801	S.D. dependent var		0.7939
S.E. of regression	0.5144	Akaike info criterion		1.5865
Sum squared resid	11.9075	Schwarz criterion		1.7409
Log likelihood	-34.8691	Hannan-Quinn criter.		1.6451
F-statistic	23.1070	Durbin-Watson stat		1.7236
Prob(F-statistic)	0.0000			
Prob(Wald F-statistic)	0.0000			

R-squared	0.6064	Mean dependent var	1.4219
Adjusted R-squared	0.5801	S.D. dependent var	0.7939
S.E. of regression	0.5144	Akaike info criterion	1.5865
F-statistic	23.1070	Durbin-Watson stat	1.7236
Prob(F-statistic)	0.0000		

The D(.) symbol indicates the first difference.
The symbol (#) indicates that the variable is lagged # period.

Residential Electricity Customer Model – Orange County

Dependent Variable: D(ORCUST)
Method: Least Squares
Sample: 2002Q1 2014Q1
Included observations: 49

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
Intercept	1.1719	0.0993	11.7995	0.0000
D(OCET(-1))	0.0138	0.0054	2.5451	0.0144
D(OCPOP(-10))	0.0070	0.0167	0.4218	0.6752
OCDUMMY	0.0466	0.1111	0.4199	0.6766
R-squared	0.2193	Mean dependent var		1.2367
Adjusted R-squared	0.1673	S.D. dependent var		0.3915
S.E. of regression	0.3573	Akaike info criterion		0.8576
Sum squared resid	5.7447	Schwarz criterion		1.0120
Log likelihood	-17.0112	Hannan-Quinn criter.		0.9162
F-statistic	4.2145	Durbin-Watson stat		0.7835
Prob(F-statistic)	0.0104			

R-squared	0.2193	Mean dependent var	1.2367
Adjusted R-squared	0.1673	S.D. dependent var	0.3915
S.E. of regression	0.3573	Akaike info criterion	0.8576
F-statistic	4.2145	Durbin-Watson stat	0.7835
Prob(F-statistic)	0.0104		

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The D(.) symbol indicates the first difference.
The symbol (#) indicates that the variable is lagged # period.

Residential Electricity Customer Model – Riverside County

Dependent Variable: D(RVCUST)
Method: Least Squares
Sample: 2001Q1 2014Q1
Included observations: 53

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-1.2115	0.4913	-2.4658	0.0172
D(RVEMP)	0.0743	0.0254	2.9241	0.0052
D(RVPOP)	0.3002	0.0351	8.5449	0.0000
RVDUMMY	-0.1688	0.4489	-0.3759	0.7086
R-squared	0.7063	Mean dependent var		3.1006
Adjusted R-squared	0.6884	S.D. dependent var		2.1438
S.E. of regression	1.1968	Akaike info criterion		3.2697
Sum squared resid	70.1853	Schwarz criterion		3.4184
Log likelihood	-82.6462	Hannan-Quinn criter.		3.3269
F-statistic	39.2853	Durbin-Watson stat		0.8731
Prob(F-statistic)	0.0000			

R-squared	0.7063	Mean dependent var	3.1006
Adjusted R-squared	0.6884	S.D. dependent var	2.1438
S.E. of regression	1.1968	Akaike info criterion	3.2697
F-statistic	39.2853	Durbin-Watson stat	0.8731
Prob(F-statistic)	0.0000		

The D(.) symbol indicates the first difference.
The symbol (#) indicates that the variable is lagged # period.

Residential Electricity Customer Model – San Bernardino County

Dependent Variable: D(SBERDCUST)
Method: Least Squares
Sample: 2001Q1 2014Q1
Included observations: 53

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	0.0451	0.3457	0.1304	0.8968
D(SBERDEMP)	0.0499	0.0301	1.6567	0.1040
D(SBERDPOP)	0.2467	0.0468	5.2667	0.0000
SBERDDUMMY	1.9432	0.6315	3.0770	0.0034
R-squared	0.5269	Mean dependent var		1.9661
Adjusted R-squared	0.4979	S.D. dependent var		1.7088
S.E. of regression	1.2108	Akaike info criterion		3.2929
Sum squared resid	71.8350	Schwarz criterion		3.4416
Log likelihood	-83.2619	Hannan-Quinn criter.		3.3501
F-statistic	18.1901	Durbin-Watson stat		1.1916
Prob(F-statistic)	0.0000			

R-squared	0.5269	Mean dependent var	1.9661
Adjusted R-squared	0.4979	S.D. dependent var	1.7088
S.E. of regression	1.2108	Akaike info criterion	3.2929
F-statistic	18.1901	Durbin-Watson stat	1.1916
Prob(F-statistic)	0.0000		

The D(.) symbol indicates the first difference.
The symbol (#) indicates that the variable is lagged # period.

Residential Electricity Customer Model – Ventura/Santa Barbara Counties

Dependent Variable: D(VENSBCUST1)
Method: Least Squares
Sample: 2002Q1 2014Q1
Included observations: 49

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	0.0768	0.0859	0.8939	0.3761
D(VENET(-10))	0.0374	0.0137	2.7276	0.0091
D(VENPOP(-18))	0.1465	0.0308	4.7624	0.0000
VENDUMMY	0.2166	0.0952	2.2738	0.0278
R-squared	0.5128	Mean dependent var		0.5113
Adjusted R-squared	0.4803	S.D. dependent var		0.3358
S.E. of regression	0.2421	Akaike info criterion		0.0789
Sum squared resid	2.6367	Schwarz criterion		0.2333
Log likelihood	2.0681	Hannan-Quinn criter.		0.1374
F-statistic	15.7878	Durbin-Watson stat		1.3784
Prob(F-statistic)	0.0000			

R-squared	0.5128	Mean dependent var	0.5113
Adjusted R-squared	0.4803	S.D. dependent var	0.3358
S.E. of regression	0.2421	Akaike info criterion	0.0789
F-statistic	15.7878	Durbin-Watson stat	1.3784
Prob(F-statistic)	0.0000		

The D(.) symbol indicates the first difference.
The symbol (#) indicates that the variable is lagged # period.

Residential Electricity Customer Model – OTHER (RURAL) Counties

Dependent Variable: D(OTHCUST)
Method: Least Squares
Sample: 2002Q1 2014Q1
Included observations: 49

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-0.0179	0.0441	-0.4060	0.6867
D(OTHERET)	0.1204	0.0168	7.1585	0.0000
D(OTHERPOP(-1))	0.2808	0.0202	13.9113	0.0000
OTHERDUMMY	0.5870	0.0512	11.4630	0.0000
R-squared	0.9175	Mean dependent var		0.6871
Adjusted R-squared	0.9120	S.D. dependent var		0.4308
S.E. of regression	0.1278	Akaike info criterion		-1.1989
Sum squared resid	0.7347	Schwarz criterion		-1.0445
Log likelihood	33.3734	Hannan-Quinn criter.		-1.1403
F-statistic	166.8554	Durbin-Watson stat		1.8494
Prob(F-statistic)	0.0000			

R-squared	0.9175	Mean dependent var	0.6871
Adjusted R-squared	0.9120	S.D. dependent var	0.4308
S.E. of regression	0.1278	Akaike info criterion	-1.1989
F-statistic	166.8554	Durbin-Watson stat	1.8494
Prob(F-statistic)	0.0000		

The D(.) symbol indicates the first difference.
The symbol (#) indicates that the variable is lagged # period.

Commercial Customer Model – Small Customers

Dependent Variable:
D(COMCUSTS)
Method: Least Squares
Sample: 2001Q1 2014Q1
Included observations: 53

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-207.4733	188.6460	-1.0998	0.2769
D(TOTEMP)	6.6964	2.3740	2.8207	0.0069
D(COMSTOCK)	0.0977	0.0311	3.1399	0.0029
D(TOTALRESCUST(-1))	144.9288	36.6044	3.9593	0.0002
COMCUSTS_DUMMY	16,715.2300	421.0916	39.6950	0.0000
R-squared	0.9571	Mean dependent var		2,558.8870
Adjusted R-squared	0.9536	S.D. dependent var		2,798.2570
S.E. of regression	603.0258	Akaike info criterion		15.7314
Sum squared resid	17,454,728.0000	Schwarz criterion		15.9173
Log likelihood	-411.8817	Hannan-Quinn criter.		15.8029
F-statistic	267.9282	Durbin-Watson stat		0.9220
Prob(F-statistic)	0.0000	Wald F-statistic		11,987.9800
Prob(Wald F-statistic)	0.0000			

R-squared	0.9571	Mean dependent var	#######
Adjusted R-squared	0.9536	S.D. dependent var	#######
S.E. of regression	603.0258	Akaike info criterion	15.7314
F-statistic	267.9282	Durbin-Watson stat	0.9220
Prob(F-statistic)	0.0000		

The D(.) symbol indicates the first difference.
The symbol -#) indicates that the variable is lagged # period.

Commercial Customer Model – Large Customers

Dependent Variable:
D(COMCUSTL)
Method: Least Squares
Sample: 2001Q1 2014Q1
Included observations: 53

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-24.3628	18.5287	-1.3149	0.1947
D(TOTEMP)	0.4153	0.2217	1.8732	0.0670
D(COMSTOCK)	0.0103	0.0030	3.4431	0.0012
COMCUSTL_DUMMY	-91.1628	35.5229	-2.5663	0.0134
R-squared	0.3536	Mean dependent var		51.8491
Adjusted R-squared	0.3140	S.D. dependent var		77.2193
S.E. of regression	63.9565	Akaike info criterion		11.2268
Sum squared resid	200,431.3000	Schwarz criterion		11.3755
Log likelihood	-293.5090	Hannan-Quinn criter.		11.2839
F-statistic	8.9343	Durbin-Watson stat		1.0706
Prob(F-statistic)	0.0001	Wald F-statistic		7.0502
Prob(Wald F-statistic)	0.0005			

R-squared	0.3536	Mean dependent var	51.8491
Adjusted R-squared	0.3140	S.D. dependent var	77.2193
S.E. of regression	63.9565	Akaike info criterion	11.2268
F-statistic	8.9343	Durbin-Watson stat	1.0706
Prob(F-statistic)	0.0001		

The D(.) symbol indicates the first difference.
The symbol (-#) indicates that the variable is lagged # period.

Industrial Customer Model

Dependent Variable:
D(INDCUST)
Method: Least Squares
Sample: 2001Q1 2014Q1
Included observations: 53

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-86.3558	20.6940	-4.1730	0.0001
D(MANEMP(-1))	9.2435	2.7748	3.3312	0.0016
INDCUST_DUMMY	-480.9435	65.8595	-7.3026	0.0000
R-squared	0.6941	Mean dependent var		-257.8931
Adjusted R-squared	0.6819	S.D. dependent var		271.4794
S.E. of regression	153.1175	Akaike info criterion		12.9552
Sum squared resid	1,172,249.0000	Schwarz criterion		13.0668
Log likelihood	-340.3135	Hannan-Quinn criter.		12.9981
F-statistic	56.7330	Durbin-Watson stat		1.6802
Prob(F-statistic)	0.0000	Wald F-statistic		35.8649
Prob(Wald F-statistic)	0.0000			

R-squared	0.6941	Mean dependent var	#######
Adjusted R-squared	0.6819	S.D. dependent var	271.4794
S.E. of regression	153.1175	Akaike info criterion	12.9552
F-statistic	56.7330	Durbin-Watson stat	1.6802
Prob(F-statistic)	0.0000		

The D(.) symbol indicates the first difference.
The symbol (-#) indicates that the variable is lagged # period.

Other Public Authority Customer Model

Dependent Variable:
D(OPACUST)
Method: Least Squares
Sample: 2001Q1 2014Q1
Included observations: 53

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	-102.9263	6.9952	-14.7139	0.0000
D(OPASTOCK(-4))	0.0099	0.0057	1.7417	0.0877
OPACUST_DUMMY	-57.8215	3.3513	-17.2532	0.0000
R-squared	0.6921	Mean dependent var		-104.3396
Adjusted R-squared	0.6798	S.D. dependent var		30.1739
S.E. of regression	17.0740	Akaike info criterion		8.5679
Sum squared resid	14,576.1000	Schwarz criterion		8.6795
Log likelihood	-224.0502	Hannan-Quinn criter.		8.6108
F-statistic	56.2016	Durbin-Watson stat		1.5944
Prob(F-statistic)	0.0000	Wald F-statistic		149.1215
Prob(Wald F-statistic)	0.0000			

R-squared	0.6921	Mean dependent var	#######
Adjusted R-squared	0.6798	S.D. dependent var	30.1739
S.E. of regression	17.0740	Akaike info criterion	8.5679
F-statistic	56.2016	Durbin-Watson stat	1.5944
Prob(F-statistic)	0.0000		

The D(.) symbol indicates the first difference.
The symbol (-#) indicates that the variable is lagged # period.

Agriculture Customer Model

Dependent Variable: D(AGCUST)
Method: Least Squares
Sample: 2001Q1 2014Q1
Included observations: 53

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
Intercept	-22.7750	10.3428	-2.2020	0.0323
D(AGEMP_S2(-7))	1.1008	8.8654	0.1242	0.9017
AG_DUMMY	-121.2578	17.9233	-6.7654	0.0000
R-squared	0.5023	Mean dependent var		-50.1132
Adjusted R-squared	0.4824	S.D. dependent var		72.0215
S.E. of regression	51.8170	Akaike info criterion		10.7883
Sum squared resid	134,250.1000	Schwarz criterion		10.8998
Log likelihood	-282.8887	Hannan-Quinn criter.		10.8311
F-statistic	25.2288	Durbin-Watson stat		1.4805
Prob(F-statistic)	0.0000	Wald F-statistic		28.6374
Prob(Wald F-statistic)	0.0000			

R-squared	0.5023	Mean dependent var	-50.1132
Adjusted R-squared	0.4824	S.D. dependent var	72.0215
S.E. of regression	51.8170	Akaike info criterion	10.7883
F-statistic	25.2288	Durbin-Watson stat	1.4805
Prob(F-statistic)	0.0000		

The D(.) symbol indicates the first difference.
The symbol (-#) indicates that the variable is lagged # period.

Street Light Customer Model

Dependent Variable:
D(STRCUST)
Method: Least Squares
Sample: 2001Q1 2014Q1
Included observations: 53

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	97.2099	15.1822	6.4029	0.0000
D(TOTALRESCUST(-2))	0.9083	0.6082	1.4934	0.1416
STRCUST_DUMMY	-159.1179	35.9147	-4.4304	0.0001
R-squared	0.4715	Mean dependent var		84.6981
Adjusted R-squared	0.4504	S.D. dependent var		86.3236
S.E. of regression	63.9982	Akaike info criterion		11.2105
Sum squared resid	204,788.2000	Schwarz criterion		11.3221
Log likelihood	-294.0789	Hannan-Quinn criter.		11.2534
F-statistic	22.3040	Durbin-Watson stat		1.3168
Prob(F-statistic)	0.0000	Wald F-statistic		13.6557
Prob(Wald F-statistic)	0.0000			

R-squared	0.4715	Mean dependent var	84.6981
Adjusted R-squared	0.4504	S.D. dependent var	86.3236
S.E. of regression	63.9982	Akaike info criterion	11.2105
F-statistic	22.3040	Durbin-Watson stat	1.3168
Prob(F-statistic)	0.0000		

The D(.) symbol indicates the first difference.
The symbol (-#) indicates that the variable is lagged # period.

10) Customer Model Variable Description

Residential Customer Models

TotalResCust	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.
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)
Dummy	Binary variables equal to one or zero that are designed to capture billing irregularities in customer data.

Commercial Customer Models

ComCust Recorded number of commercial class customers. Source: SCE.

Total ResCust
Recorded number of residential class customers. Source: SCE.

D(COMSTOCK)
Commercial building total square footage. Source: McGraw-Hill..

Dummy Binary variables equal to one on one or more , and zero otherwise, that are designed to capture billing irregularities in customer data.

S A symbol after a variable name to denote small commercial class customers (generally those in the GS-1 and GS-2 rate groups).

L A symbol after a variable name to denote large commercial class customers (generally those in the TOU rate groups).

Industrial Customer Model

IndCust	Recorded number of industrial class customers. Source: SCE.
MANEMPLOY	Manufacturing employment. Source: Moody's Analytics
Dummy	Binary variables equal to one on one or more , and zero otherwise, that are designed to capture billing irregularities in customer data.

Other Public Authorities Customer Model

OPACust	Recorded number of other public authority class customers. Source: SCE.
OPAFLSTCK	Government building floor stock. Source: McGraw-Hill.
Dummy	Binary variables equal to one or zero that are designed to capture billing irregularities in customer data.

Agriculture Customer Model

AgCust	Recorded number of agriculture class customers. Source: SCE.
AgEmp	Number of persons employed in agriculture. Source: Estimated from CA Employment Development Department history.
Dummy	Binary variables equal to one on one or more , and zero otherwise, that are designed to capture billing irregularities in customer data.

Street Light Customer Model

StLtCust	Recorded number of street lighting customers. Source: SCE.
TotalResCust	Number of residential customers. Source: SCE.
Dummy	Binary variables equal to one or zero that are designed to capture billing irregularities in customer data.

11) Retail and Bundled Energy at ISO Interface

Annual retail energy at the ISO settlement point is derived by adjusting the annual retail sales forecast at the customer meter for distribution losses. Specifically, we employ a 5 year historical average loss factor to retail sales in the following way:

Annual Retail Energy @ ISO = Annual Retail Sales * (1+ DLF_R)

where DLF_R is the ratio of ISO settlement quality meter data for bundled and DA customers and retail sales at the customer meter, averaged over the most recent five year period.

Monthly retail energy at ISO is derived through a series of steps that begins with the annual retail energy forecast. Annual retail energy is first distributed to each hour in the year using a set of hourly load shape equations. The load shapes are derived from econometric equations that relate each hour's recorded load to daily average temperature, calendar variables, such as day of week, month and holidays. Monthly energy is then derived simply by summing the hourly load associated with each calendar month. Monthly retail peak demand is determined by selecting the maximum hourly load in each calendar month.

A similar procedure is undertaken for DA load at the ISO level. DA sales at the customer meter are converted to annual energy at ISO using an average annual loss factor unique to DA sales and DA energy. That is, annual DA Energy @ ISO = Annual DA Sales * (1+ DLF_{DA}) where where DLF_{DA} is the ratio of ISO settlement quality meter data for DA customers and DA sales at the customer meter, averaged over the most recent 5 year period. Annual DA energy is then allocated to each hour in a year using a set of hourly load shape equations that are unique to DA customers. The DA load shapes are also derived from econometric equations that relate each hour's recorded load to daily average temperature, calendar variables, such as day of week, month and holidays. Monthly DA energy is derived by summing the hourly load associated with each calendar month and monthly DA peak demand is determined by selecting the maximum hourly load in each calendar month. Bundled hourly load at ISO is then the difference between Retail and DA load in each hour of the year.

12) SCE System Energy at Generation

SCE System energy consists of retail customer energy plus wholesale transmission over the SCE system to the seven Resale Cities and six Municipal Departing Load cities (Azusa, Victorville, Rancho Cucamonga, Moreno Valley, Corona and City of Industry).

Annual system energy at generation is derived by adjusting the annual system forecast at the customer meter for distribution and transmission losses. Specifically, we employ a 5 year historical average loss factor to retail sales in the following way:

Annual System Energy @ Generation = (Annual Retail Sales+ Resale City Sales + MDL) * (1+ DLF + TLF)

where DLF_R is the ratio of ISO settlement quality meter data for bundled and DA customers and retail sales at the customer meter, averaged over the most recent five year period and TLF is the average transmission loss factor over the latest five year period. .

Monthly system energy at generation is derived through a series of steps that begins with the annual system energy forecast. Annual system energy is first distributed to each hour in the year using a set of hourly system load shape equations. The load shapes are derived from econometric equations that relate each hour's recorded load to daily average temperature, calendar variables, such as day of week, month and holidays. Monthly energy is then derived simply by summing the hourly load associated with each calendar month.

13) Incorporation of Energy Efficiency Impacts in Peak Demand Forecasting

SCE employs a separate forecasting methodology in order to forecast annual peak demand.

The annual peak forecast model relates observed base load (intercept term in the regression model) and weather sensitive components (coefficient representing MW of demand per degree day over 75 degrees on an august weekday) for of annual peak demand to retail sales and customers in the SCE service area:

$BaseloadDemand_{A,T} = f(RetailSales_{A,T})$

$WeatherSensDemand_{A,T} = f(RetailCust_{A,T})$

$PeakDemand_{A,T} = BaseloadDemand_{A,T} + WeatherSensDemand_{A,T}$

where A denotes annual, T is the year, ResSales and RetailCust are year-end retail sales and year end residential and commercial customers.

The annual peak forecast methodology does not explicitly include EE occurring on the peak hour, but instead implicitly captures the observed impact of energy savings on peak demand over the historical sample period. Further, since the retail sales forecast does explicitly capture future EE impacts, and since future growth in the base load component of peak demand is directly tied to retail sales growth, future incremental EE impacts are also captured. The Weather sensitive component of peak demand is associated with customer growth rather than sales growth in order to reflect an inelastic response to economic and policy variables on the part of customers during peak day temperature conditions.

14) Economic and Demographic Projections

Residential Electricity Sales - Economic and Demographic Drivers
Average Annual Rates of Change

	Customers	Electric Rate	Thermal & Solar ByPass	Real GDP	Resid. Size (LA)
2003-2013	0.8	2.1	52.5	1.6	0.2
2013-2018	0.2	4.8	38.3	2.6	0.2
2013-2026	0.5	3.3	22.7	2.0	0.2

Commercial Electricity Sales - Economic and Demographic Drivers
Average Annual Rates of Change

	Customers	Electric Rate	Thermal & Solar ByPass	Com. Empl	Com. Floor Stock
2003-2013	1.2	0.2	15.5	1.1	1.3
2013-2018	1.2	3.5	14.7	1.7	0.6
2013-2026	1.2	2.7	10.2	1.0	0.7

Industrial Electricity Sales - Economic and Demographic Drivers
Average Annual Rates of Change

	Customers	Electric Rate	Thermal & Solar ByPass	Manuf. Empl	Man. Floor Stock
2003-2013	-5.2	-1.1	2.5	-2.6	-0.4
2013-2018	-2.4	3.6	6.3	0.1	-0.5
2013-2026	-1.7	2.7	3.0	-0.4	-0.5

15) Forecast Calibration Procedures

Calibration is typically a procedure relevant to end use models. As discussed above, SCE uses econometric models for its estimation and forecasting. With econometric models, calibration, in a sense, occurs automatically in that the models attempt to calculate the best fit to historical data. Because SCE has a relatively large sample of historical data, such as recorded sales, weather, number of billing days, etc., we are confident that our models accurately explain variation in recorded sales over time. As shown above, the amount of variation explained by our econometric models is typically between 95 to 99 percent.

16) Hourly Loads by Sub Area

The forecasts presented here do not include hourly load by geographical area.