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April 16, 2009

California Energy Commission
Docket Office
1516 Ninth Street, MS-4
Sacramento, CA 95814-5512

Attention: **Docket 09-IEP-1C**

Dear Docket Office:

SCE is resubmitting Demand Form 4 of the 2009 IEPR with corrections to the Electricity Conservation and Self-Generation sections.

Should you have any questions, please do not hesitate to contact me at (916) 441-2369.

Sincerely,

/s/ Manuel Alvarez
Manuel Alvarez
Manager, Regulatory Policy & Affairs

Electricity Demand Forecast Forms

California Energy Commission 2009 Integrated Energy Policy Report Docket Number 09-IEP-1C

Corrected Form 4

SCE Retail Sales, Energy and Demand Forecast Methodology

SOUTHERN CALIFORNIA EDISON®

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April 16th, 2009

SCE is resubmitting Demand Form 4 of the 2009 IEPR with corrections to the following sections:

- **Electricity Conservation**
- **Self-Generation**

1) Introduction

SCE uses econometric models to forecast monthly retail electricity sales (billed recorded sales measured at customer meters) by customer class. Retail sales are final sales to both bundled and direct access customers within the SCE service territory. It excludes sales to public power customers, contractual sales, or inter-changes with other utilities. CCA and other departed load are not part of the forecast process, at this time.

The retail sales forecast represents the sum of sales in seven customer classes: residential, commercial, industrial, other public authority, agriculture, street lighting and inter-department transfers (IDT). Each customer class forecast (with the exception of IDT) 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. The forecast of IDT sales, which represents a very small percentage of total retail sales, is based upon a simple average of recorded monthly sales that occurred over the most recent 14 month period. Customer class data are used because they have been defined in a consistent manner throughout the sample period used in the econometric estimation.

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 typical 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, with the exception of residential customers. Residential customers are forecast using a stock adjustment model that transforms housing starts into new customer additions taking into consideration vacancy rates and demolition rates (more detail is provided in Section 9 below).

The regression equations, along with forecasts of the economic drivers provided principally by Global Insight and McGraw-Hill, and normal weather conditions and normal billing days, are used to predict sales by revenue 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 customers accounted for 9,300 GWh of sales in 2007 (about 10.5 percent of retail sales). This sales level is assumed to remain approximately constant throughout the forecast. DA sales are subtracted from the retail sales forecast in order to derive to the forecast of SCE bundled customer sales. Bundled energy at the ISO settlement point is then derived by adjusting the annual bundled sales forecast for distribution losses.

2) Forecast Assumptions and Drivers

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

Employment Growth in Southern California

Employment growth in Southern California has slowed considerably over the past two years. As of March 2008, the year over year percent change in total Non-Farm employment growth was -0.7 percent. Peak employment growth during the current expansion phase of the business cycle occurred in February 2006, when year over year growth in Non-Farm employment reached 2.7 percent.

A major reason for the slowing employment growth trend in Southern California is the downturn in residential housing construction. During the peak of the Southern California housing boom, year over year construction employment was growing at double-digit rates, but starting In February 2007, construction employment started to contract significantly. Also negatively affected by the housing construction slowdown is Financial Services employment. Between 2001 and 2005 Financial Service employment growth in Southern California averaged nearly 4 percent per year. However, recent data suggests that year over year Financial Service employment is contracting at a rate of -6.0 percent.

As a consequence, Commercial Service employment growth as a whole has slowed dramatically over the past year. Year over year growth in service employment was in the 2 percent range as recently as January 2007, but by March 2008, commercial service employment growth was at a standstill – showing zero growth between January and March 2008. The only sectors that have maintained relatively strong employment growth up to March of this year include Education and Health Care and Government.

According to Global Insight, total non-farm employment growth will remain around zero in 2008 and 2008. In the key sectors that most directly impact future retail electricity sales, we are forecasting 0.4 percent annual growth for Commercial Services in 2008 and 2.4 percent average annual growth in 2009. Job losses are expected to continue in the Southern California manufacturing sector – about a one percent decline per year in each of 2008 and 2009. These projections are similar to the declines in manufacturing employment experienced in 2004 to 2006. Finally, Government employment growth is expected to average about one percent per year between 2006 and 2009, which is about equal to Government employment growth in 2006.

We use employment per square foot to explain how electricity consumption varies in response to changing economic conditions. It turns out that a change in employment per square foot is 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 square foot increases electricity use because an increase in employment is associated with an increase in energy using office and factory machines and equipment.

Changes in employment per square foot cause both seasonal variations in electricity consumption and changes in the longer term trend rate of growth in consumption over the forecast period.

Weather

SCE uses 30 year average temperature conditions as its definition of normal weather. Normal weather conditions are assumed throughout the forecast period. For purposes of model estimation and forecasting, actual and normal temperature data are transformed into cooling and heating degree days. 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 in Section 4 below.

Billing Days

The number of days for which a customer is billed can vary depending upon meter reading schedules. Recorded sales will therefore vary with the number of billing days. 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 provides 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 using an average unit revenue price with a one period lag (with the exception of the industrial electricity consumption model, which does use current period rates). 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 short-run elasticities are generally -.1 or smaller.

Electricity Conservation Programs

SCE's Demand-Side Management (DSM) Planning & Integration group produces the company's forecasts of energy efficiency and demand response savings. SCE's energy efficiency forecast is consistent with the CPUC's energy efficiency targets, and reflects the fact that SCE plans to meet or exceed the CPUC's energy efficiency targets over each three year EE program cycle. Committed EE is not distinguished from uncommitted EE in developing SCE's sales forecast.

For the 2009 IEPR, SCE's EE forecast is based on multiple data sources, each reflecting the best information available for specific periods during the forecast period. Historical results through 2007 are based on SCE's Energy Efficiency Annual Reports ("May 1 Report)[1] and Low Income Energy Efficiency Annual Reports. Forecasted 2008 results are based on projected year-end results by SCE energy efficiency program planners.[2] Through 2008 the historical energy efficiency savings used in SCE's sales forecast reflect net results.

SCE's energy efficiency forecast for the period 2009 - 2011 is based on a three year ramp up to SCE's energy efficiency goals ordered in D.04-09-060. Consistent with CPUC direction, savings impacts for SCE's Low Income Energy Efficiency (LIEE) Program are counted toward the EE goals.[3] As ordered in D.08-07-047, IOU EE goals for 2009 – 2011 are gross, not net of free riders.[4]

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[1] There was no Energy Efficiency Annual Report in 2008 for the 2007 program year. Consequently the data for 2007 are based on SCE's 4th Quarter 2007 Energy Efficiency Report, submitted to the CPUC on March 7, 2008.

[2] SCE's 2008 projected year end results were developed in November 2008 to enable an on time filing of SCE's 2009 IEPR Demand Forms.

[3] D.04-09-060, FOF #13

[4] D.08-07-047, OP #4

For the period 2012 – 2020, SCE's energy efficiency forecast reflects the Total Market Gross (TMG) energy efficiency goals ordered in D.08-07-047.[5] These Total Market Gross goals include EE savings from the following sources:

- IOU EE programs
- State and Federal standards
- Big Bold Energy Efficiency Strategies (BBEES)
- Huffman Bill (AB1109)

For consistency with historical EE data series, SCE's Demand Forecasting group translates forecasted gross savings from SCE programs for 2009 – 2020 into net equivalent values to use in developing SCE's sales forecast. SCE's estimates of EE are developed at the sector and measure level through 2011. The Total Market Gross energy efficiency goals ordered by the CPUC for 2012 – 2020 were not disaggregated by sector or end use. So that the Total Market Gross goals could be used in its sales forecast, SCE allocated the TMG goals by sector assuming roughly the same sectoral savings percentages as the 2008 Itron energy efficiency potential study.[6]

[5] D.08-07-047, OP #1
[6] California Energy Efficiency Potential Study, Itron, Inc., 2008

SCE Energy Efficiency Forecast by Sector
Annual Net GWh Equivalents

	2008	2009	2010	2011
Residential	587.3	299.9	435.5	544.7
Commercial	516.2	286.0	423.1	512.9
Industrial	167.7	94.1	140.2	170.2
Total	1,271.2	680.1	998.8	1,227.8

The forecast annual and monthly energy efficiency savings are provided in Excel file 'Energy Efficiency Summary.xls'. The monthly energy efficiency savings are estimated by distributing the annual savings using hourly load shapes based on the historical hourly energy data starting in1998. The hourly data is aggregated into monthly data. Please note the differences between the sum of the incremental energy efficiency savings and the cumulated energy efficiency savings are represented by estimated program decay. Program decay reflects instances where efficient appliances or measures are not replaced by similarly or more efficient appliances or measures. Replacement by similarly efficient appliances or measures is represented by efficiency persistence.

SCE's demand reduction programs include both reliability and price responsive programs. Reliability programs include the Time-of-Use Base Interruptible Program (TOU-BIP), Summer Discount Plan (Residential A/C Cycling, Commercial A/C Cycling), and , Agricultural and Pumping Interruptible Program. SCE's price response programs include the Capacity Bidding Program, Demand Bidding Program, Critical Peak Pricing (CPP), and Real Time Pricing (RTP). SCE's demand response programs are forecasted to reduce demand by an annual average of approximately 2,000 MW during the years 2009 - 2011. The impacts of these programs are reported as resources in the SCE's long-term procurement plan.

Real Income

Real income serves much the same purpose in the residential electricity consumption model that employment does in the commercial and industrial electricity consumption models: Changes in real income 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 2000 to 2006 period – a period of economic contraction and recovery.

Self Generation

The forecast of bypass co-generation is calculated from two lists of customers operating generating systems interconnected to the grid for the purpose of meeting their own energy requirements: a thermal list and a solar list. Both lists consist of those facilities having 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 550 operational thermal systems ranging in size from 1KW to 76 Megawatts (MW) within the SCE service area. The forecast for 2008 includes generation facilities currently in the pipeline while 2009 assumes the installations will mirror the historical trend. Thirty-one MW are added in 2008 and 25 MW in 2009 and beyond.

There are approximately 4,300 operational solar systems ranging in size from 1KW to 630 KW within the SCE service area. The forecast for 2008 includes solar facilities currently in the pipeline. The projections of solar bypass for the year 2009 and beyond are based upon an analysis of recent trends in residential and non-residential solar PV installations.

Both lists are used to estimate annual energy production which is then allocated to the months. For the 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 for each month to provided a monthly thermal parameter used in the sales forecasting models.

For the solar generation, the annual energy, for the historical period is calculated using the bypass capacity and an annual capacity factor for all hours of the year. For the post 2007 the capacity and energy are taken directly from the 2006 LTPP. The annual energy is distributed to the months using monthly capacity factors 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.

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:

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

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

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.

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 then 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:

$$Y_t = x_t' ß + e_t$$

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:

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

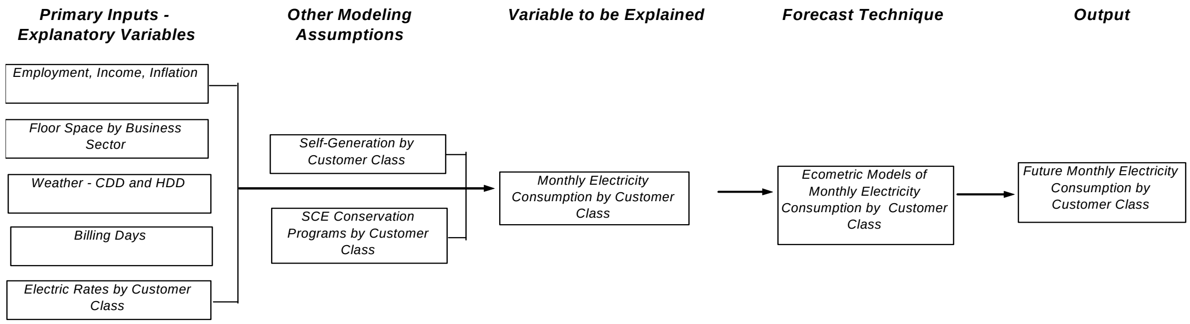
where s is the standard error of regression. These standard errors account for both innovation uncertainty (the first term) and coefficient uncertainty (the second term). Point forecasts made from linear regression models estimated by least squares are optimal in the sense that they have the smallest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

Exogenous Variable Uncertainty

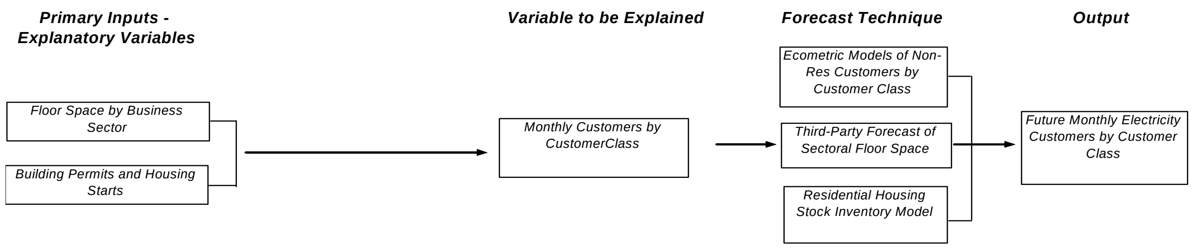
Exogenous variable uncertainty, i.e., uncertainty regarding future weather conditions, economic conditions, etc. is handled through the construction of forecast scenarios. For example, we typically include along with a base case forecast, high and low weather condition forecasts, as well as alternative high and low economic case forecasts.

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

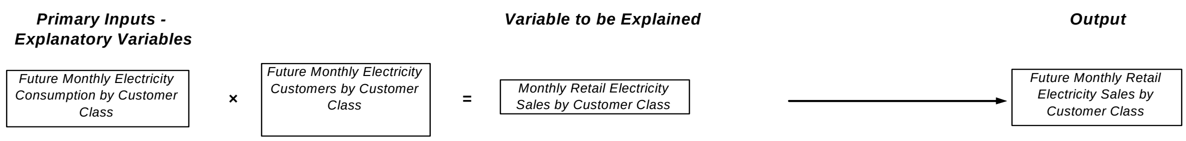
Electricity Consumption (kWh per Customer) Modeling and Forecasting



Electric Customer Modeling and Forecasting



Retail Sales Modeling and Forecasting



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

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

Dependent Variable: RESUSE+RESPROG
Method: Least Squares
Sample (adjusted): 1991M02 2008M04
Included observations: 207 after adjustments

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
INTERCEPT	-87.26951	52.87946	-1.650348	0.1005
CDDY*SUMSEAS*HSLDSIZE	0.000301	5.09E-06	59.08728	0.0000
HDDY*WINSEAS*HSLDSIZE	0.000147	6.54E-06	22.45713	0.0000
BDAYS	0.912718	0.036714	24.86026	0.0000
RESRATE(-1)*CRISIS	-9.774572	1.758532	-5.558369	0.0000
RESRATE(-1)*NOCRISIS	-8.065795	1.848495	-4.363438	0.0000
RYPRPOP	0.002982	0.001002	2.975319	0.0033
WEALTH	12.45206	1.405031	8.862485	0.0000
MAR	-15.85943	4.207572	-3.769260	0.0002
APR	19.92363	4.455813	4.471379	0.0000
NOV	12.86513	4.185833	3.073494	0.0024
B0798	-42.12440	15.35551	-2.743277	0.0067
B1299	67.09774	16.71516	4.014184	0.0001
B0305	70.42349	16.00527	4.400019	0.0000
B0907	-90.70516	15.91594	-5.699015	0.0000
B0308	-37.88133	15.97923	-2.370660	0.0188

R-squared	0.975743	Mean dependent var	576.1671
Adjusted R-squared	0.973838	S.D. dependent var	93.88844
S.E. of regression	15.18625	Akaike info criterion	8.352802
Sum squared resid	44048.86	Schwarz criterion	8.610404
Log likelihood	-848.5150	F-statistic	512.1936
Durbin-Watson stat	1.997437	Prob(F-statistic)	0.000000

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

Commercial Electricity Use Model

Dependent Variable: COMUSE+COMPROG
Method: Least Squares
Sample: 1993M03 2008M04
Included observations: 182

Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
INTERCEPT	-8.636495	0.755620	-11.42968	0.0000
CDDY*COMSIZE*SUMSEAS	7.68E-07	2.82E-08	27.29299	0.0000
COMEMPLOY	6.140425	0.391298	15.69244	0.0000
COMRATE(-1)*NOCRISIS	-0.033451	0.010813	-3.093583	0.0023
COMRATE(-1)*CRISIS	-0.053651	0.010817	-4.959709	0.0000
BDAYS	0.009270	0.000478	19.41068	0.0000
JAN	-0.360629	0.061516	-5.862367	0.0000
MAR	-0.146531	0.051965	-2.819817	0.0054
OCT	0.312865	0.052229	5.990241	0.0000
DEC	-0.227388	0.054831	-4.147040	0.0001
B0798	-1.225722	0.180922	-6.774855	0.0000
B1298	0.893155	0.185701	4.809635	0.0000
B0801	0.974658	0.200210	4.868175	0.0000
B0898	0.714346	0.184025	3.881785	0.0001
B0998	-0.538029	0.183326	-2.934828	0.0038
B0907	-0.919054	0.186327	-4.932467	0.0000
B0706	-0.790512	0.187211	-4.222563	0.0000

R-squared	0.939265	Mean dependent var	7.097577
Adjusted R-squared	0.933375	S.D. dependent var	0.691919
S.E. of regression	0.178596	Akaike info criterion	-0.518626
Sum squared resid	5.262945	Schwarz criterion	-0.219350
Log likelihood	64.19494	F-statistic	159.4820
Durbin-Watson stat	1.974749	Prob(F-statistic)	0.000000

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

Industrial Electricity Use Model

Dependent Variable: INDUSE+INDPROG
Method: Least Squares
Sample: 1994M01 2008M04
Included observations: 172

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
INTERCEPT	0.256803	0.357793	0.717741	0.4740
CDDX*SUMSEAS	0.001299	0.000164	7.926043	0.0000
INDRATE*CRISIS	-0.051461	0.008542	-6.024407	0.0000
INDRATE*NOCRISIS	-0.038407	0.010089	-3.807005	0.0002
MANEMPLOY	1.050425	0.147093	7.141235	0.0000
BDAYS	0.003243	0.000284	11.41147	0.0000
TR	-0.001755	0.000312	-5.618116	0.0000
JAN	-0.191875	0.032948	-5.823634	0.0000
AUG	0.175168	0.039677	4.414860	0.0000
OCT	0.168194	0.029609	5.680445	0.0000
B0896	-0.368109	0.107457	-3.425647	0.0008
B0598	-0.402913	0.103887	-3.878367	0.0002
B1299	0.443394	0.114046	3.887838	0.0001
B0799	-0.262229	0.103433	-2.535263	0.0122
B0899	0.268415	0.108246	2.479680	0.0142
B0901	0.545634	0.118376	4.609342	0.0000
B0801	0.305679	0.120975	2.526800	0.0125
B0807	-0.274604	0.108518	-2.530484	0.0124

R-squared	0.893470	Mean dependent var	3.549006
Adjusted R-squared	0.881710	S.D. dependent var	0.296006
S.E. of regression	0.101806	Akaike info criterion	-1.632733
Sum squared resid	1.596130	Schwarz criterion	-1.303344
Log likelihood	158.4151	F-statistic	75.97662
Durbin-Watson stat	2.187074	Prob(F-statistic)	0.000000

Other Public Authority Electricity Use Model

Dependent Variable: OPAUSE+OPAPROG
Method: Least Squares
Sample (adjusted): 1993M01 2008M04
Included observations: 184

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
INTERCEPT	0.848516	0.205316	4.132725	0.0001
CDDX*SUMSEAS	0.002847	0.000103	27.68469	0.0000
OPARATE(-1)	-0.022543	0.004675	-4.822131	0.0000
GOVEMPLOY	0.206361	0.052068	3.963333	0.0001
BDAYS	0.001616	0.000186	8.696324	0.0000
TR	-0.002167	0.000107	-20.21200	0.0000
JAN	-0.078386	0.023784	-3.295735	0.0012
JUN	0.160992	0.020613	7.810045	0.0000
OCT	0.242910	0.022879	10.61729	0.0000
NOV	0.168482	0.023536	7.158621	0.0000
B0597	0.871788	0.073005	11.94150	0.0000
B0797	-0.816672	0.073583	-11.09860	0.0000
B1098	0.402241	0.075246	5.345678	0.0000
B0899	0.529757	0.073043	7.252623	0.0000
B0996	0.340481	0.073961	4.603501	0.0000
B0706	-0.359928	0.075527	-4.765574	0.0000
B0199	0.346494	0.075086	4.614647	0.0000
B0798	-0.193368	0.073633	-2.626095	0.0095
B1198	-0.374561	0.076046	-4.925471	0.0000
B0896	-0.327328	0.074472	-4.395309	0.0000
B0901	0.256454	0.076687	3.344147	0.0010
B0803	-0.190668	0.074877	-2.546423	0.0118
B0907	-0.276281	0.075235	-3.672215	0.0003

R-squared	0.939608	Mean dependent var	2.264038
Adjusted R-squared	0.931356	S.D. dependent var	0.276336
S.E. of regression	0.072400	Akaike info criterion	-2.296742
Sum squared resid	0.843932	Schwarz criterion	-1.894875
Log likelihood	234.3002	F-statistic	113.8596
Durbin-Watson stat	1.754647	Prob(F-statistic)	0.000000

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

Agriculture Electricity Use Model

Dependent Variable: AGUSE+AGPROG
Method: Least Squares
Sample: 1992M06 2008M04
Included observations: 191

Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
INTERCEPT	-1.627022	0.699238	-2.326851	0.0212
AGRATE(-1)	-0.072548	0.026834	-2.703627	0.0076
BDAYS	0.007234	0.000916	7.895265	0.0000
RUNOFF	-0.001933	0.000221	-8.753773	0.0000
TR	0.009897	0.000648	15.28317	0.0000
APR	1.382260	0.123576	11.18555	0.0000
MAY	2.464533	0.150634	16.36109	0.0000
JUN	3.289963	0.136183	24.15849	0.0000
JUL	3.677996	0.123288	29.83256	0.0000
AUG	3.893752	0.120103	32.42016	0.0000
SEP	2.975521	0.119033	24.99740	0.0000
OCT	1.961015	0.118311	16.57502	0.0000
NOV	0.678194	0.118628	5.716959	0.0000
B0699	-2.002894	0.423364	-4.730906	0.0000
B0398	1.409573	0.413202	3.411339	0.0008
B0498	-2.379489	0.423090	-5.624076	0.0000
B0598	-1.065986	0.423150	-2.519168	0.0127
B0799	-1.442767	0.422399	-3.415648	0.0008
B0302	1.274418	0.413705	3.080501	0.0024
B0698	-1.610742	0.423130	-3.806728	0.0002
B0807	1.034265	0.426805	2.423273	0.0164
B0208	-0.992854	0.300440	-3.304670	0.0012

R-squared	0.946807	Mean dependent var	4.633298
Adjusted R-squared	0.940197	S.D. dependent var	1.669122
S.E. of regression	0.408177	Akaike info criterion	1.153759
Sum squared resid	28.15680	Schwarz criterion	1.528366
Log likelihood	-88.18398	F-statistic	143.2437
Durbin-Watson stat	1.640027	Prob(F-statistic)	0.000000

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

Street Light Electricity Use Model

Dependent Variable: STLTUSE
Method: Least Squares
Sample: 2001M06 2008M04
Included observations: 83

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
INTERCEPT	0.135024	0.167324	0.806959	0.4224
BDAYS	0.001136	0.000147	7.702396	0.0000
RESPRSTLT	0.007369	0.000431	17.11052	0.0000
JAN	0.111157	0.020210	5.500200	0.0000
FEB	0.092927	0.021072	4.409982	0.0000
MAR	0.062392	0.017195	3.628594	0.0005
OCT	0.049641	0.016858	2.944656	0.0044
NOV	0.093389	0.020066	4.654012	0.0000
DEC	0.130727	0.019191	6.811991	0.0000
B0506	0.124277	0.039801	3.122429	0.0026
B1106	-0.198682	0.043090	-4.610884	0.0000
AR(1)	0.354616	0.116718	3.038243	0.0033

R-squared	0.929162	Mean dependent var	3.247711
Adjusted R-squared	0.918187	S.D. dependent var	0.144444
S.E. of regression	0.041315	Akaike info criterion	-3.402168
Sum squared resid	0.121194	Schwarz criterion	-3.052457
Log likelihood	153.1900	F-statistic	84.66253
Durbin-Watson stat	1.994473	Prob(F-statistic)	0.000000

The AR(1) indicates the equation is adjusted for first order serial correlation.

8) Electricity Use Model Variable Description

Residential Electricity Use Model

ResUse	Residential class monthly electricity consumption in kWh per customer. Source: SCE.
CDDY	Cooling degree-days, dynamic population share weighted. Source: SCE and National Weather Service.
HDDY	Heating degree-days, dynamic population share weighted. Source: SCE and National Weather Service.
ResRate(-1)	Residential constant $2000 dollar price of electricity in cents per kWh in previous month. Source: SCE and Global Insight.
ResProg	SCE residential class monthly energy conservation program and by-pass avoided consumption in kWh per customer. Source: SCE.
RYprPop	Constant $2000 dollar total income per capita. Source: SCE and Global Insight.
BDays	Average number of days in monthly billing statement multiplied by the number of billing cycles in month. Source: SCE
Mar	Binary variable set equal to 1 for the month of March and zero otherwise.
Apr	Binary variable set equal to 1 for the month of April and zero otherwise.
Nov	Binary variable set equal to 1 for the month of November and zero otherwise.
Crisis	Binary variable set equal to one for the period February 2001 to January 2002 and zero otherwise.
NoCrisis	Binary variable set equal to zero for the period February 2001 to January 2002 and one otherwise.
Wealth	Binary variable with a starting value of one between January 2004 and December 2004, a value of 2 between January and December 2005, a value of 3.5 between January and December 2006, a value of 3.25 from January 2008 to August 2008, and value 0f 3.25 thereafter.
Bmmyy	Binary variables equal to one in a particular month and year, and zero otherwise, that are designed to capture billing irregularities in sales data.
HsldSize	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.

Commercial Electricity Use Model

ComUse	Commercial class monthly electricity consumption in MWh per commercial customer. Source: SCE.
CDDY	Cooling degree-days, dynamic population share weighted. Source: SCE and National Weather Service
ComRate(-1)	Commercial class constant $2000 dollar price of electricity in cents per kWh in previous month. Source: SCE and Global Insight
ComEmploy	Commercial service monthly employment per thousand commercial building square feet. Source: Global Insight and McGraw-Hill.
ComProg	SCE commercial class monthly electricity conservation program and by-pass avoided consumption in MWh per customer. Source: SCE.
ComSize	Average commercial building size in square feet. Source: McGraw-Hill and SCE.
BDays	Average number of days in monthly billing statement multiplied by the number of billing cycles in month. Source: SCE
Jan	Binary variable set equal to 1 for the month of January and zero otherwise.
Mar	Binary variable set equal to 1 for the month of March and zero otherwise
Oct	Binary variable set equal to 1 for the month of October and zero otherwise.
Dec	Binary variable set equal to 1 for the month of December and zero otherwise.
Bmmyy	Binary variables equal to one in a particular month and year, and zero otherwise, that are designed to capture billing irregularities in sales data.
SumSeas	A binary equal to 1 during the summer months April to October and zero otherwise.
Crisis	Binary variable set equal to one for the period February 2001 to January 2002 and zero otherwise.
NoCrisis	Binary variable set equal to zero for the period February 2001 to January 2002 and one otherwise.

Industrial Electricity Use Model

IndUse	Industrial class monthly electricity consumption in kWh per industrial building square feet. Source: SCE and McGraw-Hill.
CDDX	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 in current month. Source: SCE and Global Insight.
ManfEmploy	Manufacturing sector monthly employment per thousand industrial building square feet. Source: Global Insight and McGraw-Hill.
IndProg	SCE industrial class monthly electricity conservation program and by-pass avoided consumption in kWh per industrial building square feet. Source: SCE and McGraw-Hill.
BDays	Average number of days in monthly billing statement multiplied by the number of billing cycles in a month. Source: SCE
TR	Linear counter variable designed to capture secular trend in industrial class electricity consumption not otherwise captured in the model.
Jan	Binary variable set equal to 1 for the month of January and zero otherwise.
Aug	Binary variable set equal to 1 for the month of August and zero otherwise.
Oct	Binary variable set equal to 1 for the month of October and zero otherwise.
Bmmyy	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in sales data.
SumSeas	A binary equal to 1 during the summer months April to October and zero otherwise.
Crisis	Binary variable set equal to one for the period February 2001 to January 2002 and zero otherwise.
NoCrisis	Binary variable set equal to zero for the period February 2001 to January 2002 and one otherwise.

Other Public Authority Electricity Use Model

OPAUse	Other Public Authority class monthly electricity consumption in kWh per government building square feet. Source: SCE and McGraw-Hill.
CDDX	Cooling degree-days, static population weighted. Source: SCE and National Weather Service
OPARate(-1)	Other Public Authority class constant $2000 dollar price of electricity in cents per kWh in previous month. Source: SCE and Global Insight
OPAEmploy	Government employment per thousand government building square feet. Source: Global Insight and McGraw-Hill.
OPAProg	SCE Other Public Authority class monthly electricity conservation program and by-pass avoided consumption in kWh per government building square feet. Source: SCE and McGraw-Hill.
BDays	Average number of days in monthly billing statement multiplied by the number of billing cycles in month. Source: SCE
TR	Linear counter variable designed to capture secular trend in public authority class electricity consumption not otherwise captured in the model.
Jan	Binary variable set equal to 1 for the month of January and zero otherwise.
Jun	Binary variable set equal to 1 for the month of June and zero otherwise.
Oct	Binary variable set equal to 1 for the month of October and zero otherwise.
Nov	Binary variable set equal to 1 for the month of November and zero otherwise.
Bmmyy	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in sales data.
SumSeas	Binary equal to 1 during the summer months April to October and zero otherwise.

Agriculture Electricity Use Model

AgUse	Agriculture class monthly electricity consumption in MWh per agriculture customer. Source: SCE
AgProg	SCE agriculture monthly electricity conservation program and by-pass consumption in MWh per agriculture customer. Source: SCE
AgRate(-1)	Agriculture class constant $2000 dollar price of electricity in cents per kWh in previous month. Source: SCE and Global Insight.
BDays	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.
TR	Linear counter variable designed to capture secular trend in public authority class electricity consumption not otherwise captured in the model.
Apr	Binary variable set equal to 1 for the month of April and zero otherwise.
May	Binary variable set equal to 1 for the month of May and zero otherwise.
Jun	Binary variable set equal to 1 for the month of June and zero otherwise.
Jul	Binary variable set equal to 1 for the month of July and zero otherwise.
Aug	Binary variable set equal to 1 for the month of August and zero otherwise.
Sep	Binary variable set equal to 1 for the month of September and zero otherwise.
Oct	Binary variable set equal to 1 for the month of October and zero otherwise.
Nov	Binary variable set equal to 1 for the month of November and zero otherwise.
Bmmyy	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in sales data.

Street Lighting Electricity Use Model

StLtUse	Street light class electricity monthly consumption in MWh per street light customer. Source: SCE
ResprStLt	Number of residential customers per street lighting customers. Source: SCE.
BDays	Average number of days in monthly billing statement multiplied by the number of billing cycles in month. Source: SCE
Jan	Binary variable set equal to 1 for the month of January and zero otherwise.
Feb	Binary variable set equal to 1 for the month of February and zero otherwise.
Mar	Binary variable set equal to 1 for the month of March and zero otherwise.
Oct	Binary variable set equal to 1 for the month of October and zero otherwise.
Nov	Binary variable set equal to 1 for the month of November and zero otherwise.
Dec	Binary variable set equal to 1 for the month of December and zero otherwise.
Bmmyy	Binary variable equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in sales 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 in Section 10. 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. An independent forecast of building square feet by building type was provided by McGraw-Hill.

Residential Customers

New residential customers account for the vast majority of all new customers. The forecast of residential customer additions is forecast in multiple steps: forecasting residential building permits, lagging the building permits for construction time to calculate new residential units, and then converting residential units to active residential customers using an assumption about future residential vacancy rates.

Residential building permits – Monthly number of new dwelling units approved for construction

Completed Units – Monthly number of new residential units completed and ready for occupancy

Total Residential Units – The number of residential dwelling units including occupied and vacant units. Existing units plus newly completed units provides a monthly count of total residential units. An annual estimate of total units, obtained from the E5 – City and County Population and Housing Estimate published by the California Department of Finance (DOF) is used as a check on the estimated housing stock.

Occupied Units – The number of dwelling units inhabited by a household and is the same as the monthly number of active residential customers by definition. The number of active customers is provided by the SCE billing system.

Vacancy Rate – The rate of unoccupied units and is percentage difference between total units and active residential meters.

Forecasting residential customer growth is a multi-step process. The initial step requires the forecasting of residential construction in the SCE service area. Historical monthly building permit data is collected from cities and places within the SCE service area. Residential building permits for California are obtained from DOF and the U. S. Census Bureau (Census Bureau). Global Insight (GI) provides the annual forecast of California building permits.

Using historical SCE and California data, the GI building permit forecast is shared downed to develop a projection of annual building permits for the SCE service territory. The share is usually based on the most recent five years of data. (The forecast of residential building permits is also compared to similar GI forecast of residential households). The annual number of residential building permits is distributed to the each month based on the historical monthly share.

The conversion of residential building permits to completed units /residential meter sets consists of distributing building permits across the succeeding following months using a set of monthly lag factors. The distributing of monthly building permits to the succeeding months is an estimation of the construction period. The monthly distribution factors are estimated in a regression equation providing the following values:

Monthly Distribution Building Permits to Completions

Month	Distribution Factor
Constant	914
Lag 1	.03428
Lag 2	.03178
Lag 3	.03988
Lag 4	.04678
Lag 5	.05235
Lag 6	.05671
Lag 7	.05983
Lag 8	.06170
Lag 9	.06232
Lag 10	.06170
Lag 11	.05983
Lag 12	.05671
Lag 13	.05235
Lag 14	.04674
Lag 15	.03988
Lag 16	.03178
Lag 17	.02244
Lag 18	.01184

Completed Units represents the monthly completion of the building permits and additions to the stock of housing units. The completed units are added to the existing stock to determine the change in the total number of units. A count of total residential units and vacancy rates are available from the annual E-5 City and County Population and Housing Estimates published by DOF. This annual count is used as a check on recorded growth in the housing stock. In most years the addition of completed units/meter sets results in a number greater then the total units reported by the DOF. That difference represents the number of demolished units.

A vacancy rate is estimated by comparing the total residential units and the number of active residential customers. A forecast of vacancy rate is applied to the residential housing stock. The resulting value is the number of the active residential customers. The change in the number of active residential customers represents the additions or deductions in residential customers. The following table provides the output of the forecasting process.

Residential Building Permits and Customer Forecast

RESIDENTAIL BUILDING PERMITS, UNITS AND CUSTOMERS

(1,000's of Units)

	Building	Total Units		Active Customers		Vaccancy
Year	Permits	Total	Ann'l Change	Total	Ann'l Change	Rate
1991	34.4	3,861.7	48.5	3,600.7	40.1	6.8
1992	32.9	3,893.6	32.0	3,626.0	25.3	6.9
1993	25.9	3,924.0	30.4	3,642.3	16.3	7.2
1994	32.9	3,950.2	26.2	3,664.5	22.2	7.2
1995	27.2	3,977.7	27.4	3,692.0	27.5	7.2
1996	29.7	4,004.5	26.8	3,726.7	34.7	6.9
1997	36.3	4,040.4	35.9	3,752.2	25.5	7.1
1998	39.4	4,064.5	24.1	3,791.2	39.0	6.7
1999	45.3	4,091.4	26.9	3,843.9	52.7	6.0
2000	43.8	4,120.6	29.2	3,885.0	41.1	5.7
2001	53.1	4,160.3	39.7	3,931.4	46.4	5.5
2002	60.4	4,208.5	48.2	3,977.2	45.8	5.5
2003	68.9	4,261.0	52.5	4,030.5	53.3	5.4
2004	73.1	4,321.9	60.9	4,086.5	56.0	5.4
2005	72.1	4,388.3	66.4	4,146.1	59.6	5.5
2006	63.3	4,452.2	63.8	4,205.5	59.4	5.5
2007	33.9	4,504.4	52.2	4,234.7	29.2	6.0
2008	24.4	4,536.2	31.8	4,260.4	25.7	6.1
2009	40.7	4,566.6	30.4	4,296.3	36.0	5.9

Commercial Customer Model

Dependent Variable: D(COMCUST)
Method: Least Squares
Sample: 1995M01 2008M04
Included observations: 160

Variable	Coefficient	Std. Error	t-Statistic	Prob.
INTERCEPT	-0.332788	87.97510	-0.003783	0.9970
D(COMCUST(-1))	0.584407	0.058400	10.00692	0.0000
B0598	1390.389	323.6266	4.296276	0.0000
B0298	-2332.938	320.8321	-7.271523	0.0000
B0398	5035.741	352.8701	14.27080	0.0000
B0498	-3440.235	381.6630	-9.013801	0.0000
B1199	1387.271	319.6627	4.339796	0.0000
B0301	837.0248	320.0687	2.615141	0.0098
PDL01	9.608279	2.637119	3.643475	0.0004

R-squared	0.757080	Mean dependent var	924.7063
Adjusted R-squared	0.744210	S.D. dependent var	629.6301
S.E. of regression	318.4399	Akaike info criterion	14.41935
Sum squared resid	15311996	Schwarz criterion	14.59233
Log likelihood	-1144.548	F-statistic	58.82540
Durbin-Watson stat	2.320502	Prob(F-statistic)	0.000000

Lag Distribution of D(RESACCT)

	i	Coefficient	Std. Error	t-Statistic
. * |	0	8.40724	2.30748	3.64348
. * |	1	14.4124	3.95568	3.64348
. * |	2	18.0155	4.94460	3.64348
. *|	3	19.2166	5.27424	3.64348
. * |	4	18.0155	4.94460	3.64348
. * |	5	14.4124	3.95568	3.64348
. * |	6	8.40724	2.30748	3.64348
Sum of Lags		100.887	27.6898	3.64348

The D(.) symbol indicates the first difference.
The PDL symbol indicates a polynomial distributed lag.
The symbol (-1) indicates that the variable is lagged 1 period

Industrial Customer Model

Dependent Variable: INDCUST
Method: Least Squares
Sample (adjusted): 1991M04 2008M04
Included observations: 205

Variable	Coefficient	Std. Error	t-Statistic	Prob.
INTERCEPT	1995.782	360.6977	5.533115	0.0000
TR	-3.407980	1.205062	-2.828053	0.0052
TR^2	-0.039936	0.007061	-5.655792	0.0000
INDCUST(-1)	0.860537	0.023803	36.15179	0.0000
B1995	114.4085	30.43636	3.758940	0.0002
B2001	-226.0978	36.44078	-6.204527	0.0000
B2003	192.4541	36.43153	5.282626	0.0000
B2007	209.3980	43.93120	4.766499	0.0000
B0293	-655.0392	121.9113	-5.373082	0.0000
B0199	378.2641	73.21387	5.166563	0.0000
PDL01	0.928083	0.214793	4.320831	0.0000

R-squared	0.999674	Mean dependent var	24419.85
Adjusted R-squared	0.999657	S.D. dependent var	6496.881
S.E. of regression	120.3298	Akaike info criterion	12.47051
Sum squared resid	2808976	Schwarz criterion	12.64882
Log likelihood	-1267.228	F-statistic	59450.01
Durbin-Watson stat	0.863961	Prob(F-statistic)	0.000000

Lag Distribution of MANEMPLOY

	i	Coefficient	Std. Error	t-Statistic
. * |	0	0.74247	0.17183	4.32083
. *|	1	1.11370	0.25775	4.32083
. *|	2	1.11370	0.25775	4.32083
. * |	3	0.74247	0.17183	4.32083
Sum of Lags		3.71233	0.85917	4.32083

The ^ indicates the square of the variable.
The PDL symbol indicates a polynomial distributed lag.
The symbol (-1) indicates that the variable is lagged 1 period

Other Public Authority Customer Model

Dependent Variable: OPACUST
Method: Least Squares
Sample: 2001M01 2008M04
Included observations: 88

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	18649.84	5135.936	3.631244	0.0005
TR	-101.3091	30.50113	-3.321488	0.0014
OPACUST(-1)	0.809638	0.049214	16.45142	0.0000
B0601	-69.24987	14.42531	-4.800581	0.0000
B0701	57.76339	14.29870	4.039765	0.0001
B1207	-44.24289	14.12561	-3.132105	0.0024
B0205	-73.97867	13.89209	-5.325235	0.0000
B0104	-52.24447	14.14117	-3.694493	0.0004
B2002	-24.14098	6.669635	-3.619535	0.0005

R-squared	0.999804	Mean dependent var	34192.07
Adjusted R-squared	0.999782	S.D. dependent var	927.8306
S.E. of regression	13.71121	Akaike info criterion	8.180949
Sum squared resid	14663.79	Schwarz criterion	8.462465
Log likelihood	-349.9618	F-statistic	44256.55
Durbin-Watson stat	1.497558	Prob(F-statistic)	0.000000

Lag Distribution of OPAFLSTCK

	i	Coefficient	Std. Error	t-Statistic
. * |	0	0.00123	0.00056	2.18300
. *|	1	0.00184	0.00084	2.18300
. *|	2	0.00184	0.00084	2.18300
. * |	3	0.00123	0.00056	2.18300
Sum of Lags		0.00613	0.00281	2.18300

The PDL symbol indicates a polynomial distributed lag.
The symbol (-1) indicates that the variable is lagged 1 period

Agriculture Customer Model

Dependent Variable: AGCUST
Method: Least Squares
Sample: 1993M06 2008M04
Included observations: 179

Variable	Coefficient	Std. Error	t-Statistic	Prob.
INTERCEPT	814.9323	470.4381	1.732284	0.0850
AGCUST(-1)	0.964386	0.017643	54.66081	0.0000
AGEMPLOY	1.021375	0.274820	3.716524	0.0003
TR	-0.676943	0.410355	-1.649652	0.1008
B0599	493.1933	29.77282	16.56522	0.0000
B0699	-525.9361	31.29548	-16.80550	0.0000
AR(1)	0.548493	0.071620	7.658347	0.0000

R-squared	0.999300	Mean dependent var	23732.23
Adjusted R-squared	0.999275	S.D. dependent var	1105.072
S.E. of regression	29.75179	Akaike info criterion	9.661977
Sum squared resid	152249.1	Schwarz criterion	9.786623
Log likelihood	-857.7469	F-statistic	40899.65
Durbin-Watson stat	2.092592	Prob(F-statistic)	0.000000

The symbol (-1) indicates that the variable is lagged 1 period.
The AR(1) indicates the equation is adjusted for first order serial correlation.

Street Light Customer Model

Dependent Variable: STRCUST
Method: Least Squares
Sample: 2000M01 2007M02
Included observations: 86

Variable	Coefficient	Std. Error	t-Statistic	Prob.
INTERCEPT	-261.4340	285.3594	-0.916157	0.3620
STLTCUST(-1)	0.956817	0.017858	53.57880	0.0000
APR	18.09193	9.408951	1.922842	0.0577
AUG	-27.80061	9.911020	-2.805020	0.0062
B0101	-195.3968	27.37997	-7.136486	0.0000
B1006	-124.2965	27.27195	-4.557669	0.0000
B0202	-97.41266	27.03238	-3.603555	0.0005
B0602	-103.6865	26.97862	-3.843283	0.0002
TR	6.949852	1.800156	3.860694	0.0002
PDL01	0.019412	0.011118	1.745971	0.0842

R-squared	0.999449	Mean dependent var	12640.65
Adjusted R-squared	0.999394	S.D. dependent var	1084.822
S.E. of regression	26.71003	Akaike info criterion	9.502595
Sum squared resid	64208.32	Schwarz criterion	9.763112
Log likelihood	-465.1297	F-statistic	18135.16
Durbin-Watson stat	1.893555	Prob(F-statistic)	0.000000

Lag Distribution of RESCUST

```
                    i     Coefficient    Std. Error    t-Statistic

.   *      |        0     0.01699        0.00973       1.74597
.      *   |        1     0.02912        0.01668       1.74597
.        * |        2     0.03640        0.02085       1.74597
.         *|        3     0.03882        0.02224       1.74597
.        * |        4     0.03640        0.02085       1.74597
.      *   |        5     0.02912        0.01668       1.74597
.   *      |        6     0.01699        0.00973       1.74597

Sum of Lags               0.20383        0.11674       1.74597
```

The (-1) indicates the variable is lagged 1 period.
The PDL symbol indicates a polynomial distributed lag.

10) Customer Model Variable Description

Commercial Customer Model

ComCust	Number of commercial class customers. Source: SCE.
PDL	Polynomial distributed lag of residential customers. Source: SCE
Bmmyy	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in sales data.

Industrial Customer Model

IndCust	Number of industrial class customers. Source: SCE.
TR	Linear counter variable designed to capture secular trend growth not otherwise captured in the model.
PDL	Polynomial distributed lag of manufacturing employment. Source: Global Insight.
B1995	Binary variable equal to 1 in 1995 to 1997 and zero otherwise.
B2001	Binary variable equal to 1 in 2001 to 2003 and zero otherwise.
B2003	Binary variable equal to 1 in 2003 to 2004 and zero otherwise.
B2007	Binary variable equal to 1 in September 2006 to December 2009 and zero otherwise.
B0293	Binary variable equal to 1 in February 1993 and zero otherwise.
B0199	Binary variable equal to 1 in December 1998 to April 1999 and zero otherwise.

Other Public Authorities Customer Model

OPACust	Number of other public authority class customers. Source: SCE.
TR	Linear counter variable designed to capture secular trend growth not otherwise captured in the model.
PDL	Polynomial distributed lag of government building floor stock. Source: McGraw-Hill.
B2002	Binary variable equal to 1 in January 2001 to June 2003 and zero otherwise.
Bmmyy	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in sales data.

Agriculture Customer Model

AgCust	Number of agriculture class customers. Source: SCE.
TR	Linear counter variable designed to capture secular trend growth not otherwise captured in the model.
AgEmploy	Number of persons employed in agriculture. Source: Global Insight.
Bmmyy	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in sales data.

Street Light Customer Model

StLtCust	Number of street lighting customers. Source: SCE.
PDL	Polynomial distributed lag of number of residential customers. Source: SCE.
APR	Binary variable set equal to 1 for the month of April and zero otherwise.
AUG	Binary variable set equal to 1 for the month of August and zero otherwise.
TR	Time trend variable equal to 1 starting in June 2004 and increasing in increments to March 2006 an constant thereafter.
Bmmyy	Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in sales data.

11) Retail Energy and Retail Peak Demand at ISO Interface

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

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

where DLF is the ratio of ISO settlement quality meter data and retail sales at the customer meter, averaged over the years 2000 to 2006.

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.

Annual retail peak demand is estimated and forecast using a different procedure than that described above for monthly retail energy and monthly retail peak demand.

The procedure begins with the modeling and forecast of annual system peak. System peak includes the loads of retail customers, as well as load from various resale city customers. System peak demand is estimated and forecast as the sum of two components: base demand and weather-sensitive demand. The two components are derived from an econometric equation that relates summer season daily peak demand to daily maximum temperature and various calendar variables. The base demand is represented by the "intercept" term produced by this equation and weather sensitive demand is represented by the coefficient describing the relationship between changes in the temperature above 75 degrees and changes in that part of peak demand that is temperature sensitive during the weekdays in the month of August (an August weekday is assumed to be a likely time for the annual peak to occur).

The coefficients derived from the model described above are added to data sets consisting of base and weather sensitive coefficients estimated in past summer seasons. For system peak, these data sets comprise observations of base and weather sensitive coefficients from 1991 to 2007, with the 2007 summer season being the most recent estimate.These data sets become the dependent variables, or the variables to be explained, in another set of econometric models that estimate and forecast the change in base and weather sensitive peak demand components according to changes in the residential customer base. In other words, the observed growth in the two peak demand components is assumed to result primarily from growth in the residential customer base.

The retail annual peak is then derived by escalating the 2006 retail coefficients for base and weather sensitive demand according to forecast annual changes in the system base and weather sensitive components between 2007 and 2009

12) Incorporation of Energy Efficiency Impacts in Sales and Peak Demand Forecasting

Energy efficiency program savings are explicitly deducted in the modeling and forecasting of monthly billed retail sales. This forecast, in turn, through a series of steps, is converted into a forecast of bundled hourly load, which is necessarily also net of energy efficiency program savings.

Energy efficiency program savings (EE), measured in MWh, are explicitly included in SCE's models of electricity demand, both for model estimation and forecasting purposes. That is, electricity consumption and estimated EE enter on the "left-hand side" of our econometric equations. In this manner, we are able to construct demand equations that estimate and forecast the sum of net electricity consumption and a predetermined level of future EE.

More explicitly, we specify SCE program savings as a dependent variable in our econometric equations of electricity consumption per customer as follows:

(ResUse + ResEE) = f (CDD, HDD, Pr, Y, W, BDays)

(ComUse + ComEE) = f (CDD, Pr, Employ, BDays)

.

.

.

etc.

where ResUse is observed residential electricity consumption per customer, ResEE is estimated residential program efficiency savings per residential customer, CDD and HDD are weather variables, Pr is the average monthly electricity price, Y is real income and BDays refers to the number of days billed in the month.

The same general estimation specification is done for each of six customer classes. For example, ComUse and ComEE refer respectively to observed commercial class electricity consumption per customer and estimated commercial program efficiency savings per customer.

The reasoning behind this specification is that in the absence of SCE programs, changes in "avoided" electricity consumption will respond to changes in economic conditions, weather, and other variables in the same way as observed consumption. Since EE is predetermined in the forecast period, predicted net residential electricity consumption per customer is (ResUse + ResEE) – ResEE.

Historical DSM program impacts are provided to the Forecast Group in Energy Supply and Management by the Demand Planning Integration Group. Projected DSM program impacts are based upon CPUC approved targets.*

* CPUC Energy Savings Goals 2006 and Beyond, Decision 04-09-060, September 2004.

A forecast of total monthly billed sales (electricity consumption measured at the customer meter) is constructed as the product of forecast electricity consumption per customer and a forecast of total customers and then summing over all customer classes:

$ResUse_{t,m} \cdot ResCust_{t,m} = ResSales_{t,m}$

$ComUse_{t,m} \cdot ComCust_{t,m} = ComSales_{t,m}$

.

.

.
etc.

for each of the six customer classes, where t is a time index with t = 1, … 12, and m indicates that the data is monthly. ResCust and ComCust are the forecasts of residential and commercial class customers, respectively.

Annual sales in 2009, and other years, are then:

$RetailSales_A = \sum_m (t = 1 \ldots 12) (ResSales_{t,m} + ComSales_{t,m} + \ldots)$

where A denotes annual data.

Bundled sales are derived as:

$BundSales_A = RetailSales_A - DASales_A$

where $BundSales_A$ is annual electricity consumption by bundled customers and $DASales_A$ is annual electricity consumption by Direct Access (DA) customers. DA sales are assumed to be a constant quantity over the forecast period (and thus a declining percentage of retail sales).

Annual bundled sales at the customer meter is converted to energy measured at ISO by applying an annual average distribution loss factor (DLF):

$BundEnergy_{ISO,A} = BundSales_A \cdot DLF$

Annual bundled energy is then transformed to hourly bundled energy by use of an 8760 load shape allocation model (LS). The allocation is determined by the historical measured relationship between load and temperature throughout the year.

$BundEnergy_{ISO,h} = f(LS (Temp))$

where h is the hour (h=1, 2, … 8760) and Temp represents average daily temperature.

Monthly bundled peak demand is defined as the maximum hourly load in a calendar month:

$PeakDemand_{ISO, t=Jan} \rightarrow MAX (BundEnergy_{ISO,h}) (h=1 \ldots 744)$

$PeakDemand_{ISO, t=Feb} \rightarrow MAX (BundEnergy_{ISO,h}) (h=745 \ldots 1416)$
.
.
$PeakDemand_{ISO, t=Dec} \rightarrow MAX (BundEnergy_{ISO,h}) (h=8016 \ldots 8760)$

Note that throughout this process, from the forecast of monthly billed sales at the customer meter to the forecast of monthly bundled peak demand at ISO, all energy is net of energy efficiency program savings. Thus EE impacts are preserved in SCE's forecast of bundled peak demand in 2009 and all other years.

The only exception to the process described above is the forecast of annual peak demand – the highest hourly load in the year. SCE employs a separate forecasting methodology in order to forecast annual peak demand.

The annual peak forecast model relates observed annual peak demand to customers in the SCE service area:

$PeakDemand_{A,T} = f(ResCust_{A,T} + ComCust_{A,T})$

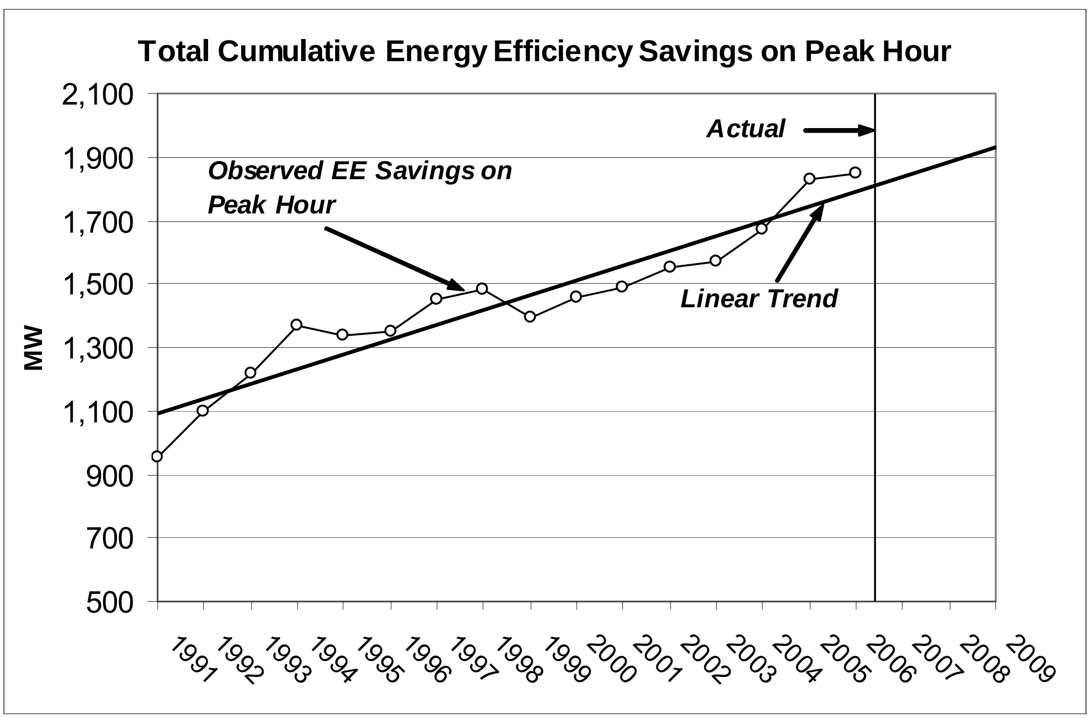
where A denotes annual peak demand, T is the year, for example 2009, and ResCust and ComCust are year-end residential and commercial class customers.

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. Thus, so long as future EE on the peak hour increase at the observed average annual rate of growth, future EE impacts on the annual peak are automatically captured in the forecast. An examination of EE savings on the peak hour between 1991 and 2006 (which represented the EE sample period available to SCE at the time of the Fall 2007 Forecast) suggests that a linear growth trend provides a reasonable forecast of future peak hour EE. Therefore, SCE's annual peak forecast is implicitly capturing a reasonable estimate of EE in the 2007 to 2009 period (about 1,925 MW in 2009 - see the diagram below).

If future analysis suggests that such implicit deductions are either too high or too low, SCE is prepared to make incremental adjustments for EE to its Peak Demand forecast in succeeding forecast implementations.

13) 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 98 percent.



14) Hourly Loads by Sub Area

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

15) Economic and Demographic Projections

Residential Electricty Use - Economic and Demographic Drivers

Average Annual Rates of Change

	Customers	Electric Rate	Conservation	ByPass	Real Income per Capita	Household Size
1991-2007	1.0%	-0.6%	10.1%	17.7%	1.3%	0.6%
2007-2012	0.5%	1.6%	8.1%	23.8%	1.5%	0.6%
2012-2020	1.4%	0.0%	4.7%	9.5%	1.6%	0.6%

Commercial Electricty Use - Economic and Demographic Drivers

Average Annual Rates of Change

	Customers	Electric Rate	Conserv	ByPass	ComEmploy	Comsize	Floor Stock
1991-2007	2.3%	-0.6%	5.3%	7.6%	1.6%	-0.4%	1.8%
2007-2012	1.0%	1.6%	3.9%	12.0%	1.2%	0.5%	1.5%
2012-2020	2.4%	0.0%	3.6%	5.8%	1.3%	-0.9%	1.5%

Industrial Electricty Use - Economic and Demographic Drivers

Average Annual Rates of Change

	Customers	Electric Rate	Conserv	ByPass	IndEmploy	IndSize	IndFlStck
1991-2007	-5.5%	-0.8%	-1.6%	2.4%	-1.9%	5.8%	-0.1%
2007-2012	-5.0%	1.6%	-2.2%	1.8%	-0.9%	5.1%	-0.1%
2012-2020	-4.6%	0.0%	1.9%	1.5%	0.0%	4.7%	-0.1%