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SCE 2013 IEPR Sales and Customer Forecast Work Papers

Form 4 Demand Forecast Methods and Models

Southern California Edison

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Electricity Demand Forecast Forms
California Energy Commission

2013 Integrated Energy Policy Report

Docket Number 13-IEP-1C

<u>Form 5</u>
SCE Committed Demand-Side Program Methodology

SOUTHERN CALIFORNIA EDISON®

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Form 5 Committed Demand-Side Program Methodology
Renewable and Distributed Generation Program Impacts

Data Sources

SCE's forecast of self-generation is developed from a list of customers operating or planning to operate generating systems interconnected to the grid for the purpose of meeting their own energy requirements. This list of customers includes self-generation projects at various stages of development, including:

- systems on-line,
- systems under construction,
- systems currently being planned for installation

The description of each self-generation project includes customer description, nameplate capacity in kilowatts (kW), probable bypass kW, capacity factor, and on-line date. The list provides both estimated bypass capacity and estimated annual energy. SCE draws from multiple internal databases in an effort to make its list of customer self-generation projects as exhaustive as possible, including SCE's customer account data, customer generation project tracking system, and Rule 21 requests for interconnection. These databases contain data regarding DG (thermal generation) customers and NEM (solar/renewable) customers.

SCE develops separate forecasts for thermal and solar/renewable systems. The methodologies used to develop each of these forecasts are described further below. These forecasts are ultimately combined for use in SCE's sales forecast.

Forecasting Methodology

Thermal Generation

There are approximately 700 operational thermal systems ranging in size from 1KW to 76 Megawatts (MW) within the SCE service area. For thermal generation, annual energy impacts are calculated using the bypass capacity and a high capacity factor for all hours of the year.

For the period 2001 – 2007, customer incentives were available for selected thermal generation. For this period the historical data for committed thermal customer generation reflect impacts both from systems installed under the SGIP as well as systems installed by customers outside of the SGIP.

Effective January 1, 2012, Assembly Bill 1150 reaffirms that the California Public Utilities Commission shall require administration of the SGIP until January 1, 2016. Given the uncertainty of the SGIP program, SCE has reported the forecasted impacts of thermal generation as uncommitted from 2015-2024 SCE is assuming an additional 11 MW of thermal generation per year after that time period with the exception of one year where SCE knows of an additional probable unit.

[1] Assembly Bill 27781 amended Public Utility Code § 379.62 relating to SGIP and limits program eligibility for SGIP incentives to qualifying wind and fuel cell distributed generation (DG) technologies, beginning January 1, 2008 through January 1, 2012. On November 21, 2008, The CPUC voted and approved advanced energy storage (AES) systems to receive SGIP incentives if coupled with an eligible DG technology under the SGIP.

The forecast for 2013 includes generation facilities currently in the pipeline. With current interconnection requests by customers, 23 MW will be added in 2013. Based on current programs and plans for three large installations, an annual average 24 MW are added in 2013 through 2024.

Solar/Renewal Generation

There are approximately 41,219 operational solar/renewable systems ranging in size from 1kW to 1030 kW within the SCE service area. For solar/renewable generation the annual energy for the historical period is calculated using the bypass capacity and an annual capacity factor.[1]

Based on recent trends and current interconnection requests by customers, approximately 103 MW additional solar generation are forecasted in 2013. Approximately, 108-115 MW of solar generation per year are added to the forecast for the period 2012 – 2016.

Decision D.06-01-024 allocated funding for CSI through 2016. Consequently SCE has reported the forecasted impacts of CSI as committed through the year 2016, and as uncommitted from 2017 – 2022.

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[1] Capacity factors used by SCE are 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

Form 5 Committed Demand-Side Program Methodology
Energy Efficiency Program Impacts

SCE has classified Energy Efficiency (EE) program results 2000-2012 as historical, 2013-2014 as committed, and 2015-2024 as program results as uncommitted.

1. Describe how the peak and energy impacts are calculated

From 2000 through 2005, SCE utilized California IOU Database for Energy Efficiency Resources (DEER) values, Evaluation Measurement and Verification (EM&V) studies, and/or engineering workpapers to estimate EE impacts and costs by measure.

In Decision 06-06-063 (June 29, 2006) the California Public Utilities Commission (CPUC) directed all California investor owned utilities to:

a) Use the Database for Energy Efficient Resources (DEER) values for peak kW and kilowatt hour (kWh) savings for those measures that are included in the DEER database.

b) Continue to use their best estimates of those values for measures that are not currently included in DEER, or for programs with measure categories rather than specific measures, such as customized rebate programs.

c) Use the following definition of peak demand savings:
The average grid level impact for a measure between 2 p.m. and 5 p.m. during the three consecutive weekday period containing the weekday temperature with the hottest temperature of the year.

Since 2006, SCE has used the DEER peak demand reduction and annual energy savings estimates as its primary resource for energy efficiency program savings. For measures not found in DEER, detailed work papers documenting savings estimates are utilized. Note that SCE also documents in workpapers measure values that are derived through averaging DEER values.

2. Describe the basis or method used to estimate how first-year impacts might change over time

The 2000-2009 historic peak and energy impact data were extracted from SCE's Annual DSM reports, Annual Energy Efficiency reports and/or CPUC Energy Efficiency Quarterly Reports.

SCE's reported peak and energy impacts are primarily *ex-ante* engineering estimates, whether the source is the DEER or SCE workpapers. For the committed period, SCE relies upon DEER and/or SCE workpapers; however, the final *ex-ante* assumptions are pending final approval by the CPUC.

3. Document the net-to-gross ratios used to convert gross measure or program impacts into net impacts

EE results for 2000-2008 were reported as net impacts, and then converted to Gross energy/demand impacts using the individual program net-to-gross ratios (NTGRs) contained in the CPUC Energy Efficiency Policy Manual.

Over the course of a program cycle, some of the NTGRs were updated based on the results of the final energy efficiency EM&V impact evaluations, which can be found on the California Measurement Advisory Council (CALMAC)[2] website.

EE results reported for 2009-2012 and 2013-2014 proposed EE program impacts (2838E) are gross impacts per the California Public Utilities Commission (CPUC) Decision 08-07-047[3]. Gross impacts were converted to net impacts utilizing the NTGRs contained in the CPUC maintained and approved DEER database.

4. Describe how the per-measure impact estimates are aggregated and how interactive effects between the measures are estimated or accounted for

SCE interpreted this question to be asking how measure level data was aggregated to the sector and program categories.

SCE deployed a bottom up methodology designed to aggregate EE impacts and costs to the sector and program level. SCE started by determining the energy/demand and costs measure level impacts (described in question 1 above). To calculate the sector and program measure level impacts, the per measure savings estimates (energy, demand and costs) were multiplied by the number of measure installations attributable to a mutually exclusive program and sector in a given year.

SIC/NAICS codes were used to allocate EE savings to the sector level where crosscutting EE programs and measures transcended multiple sectors. By using SIC/NAICS codes, SCE was able to allocate energy/demand savings and costs into mutually exclusive sector grouping (Residential, Commercial, and Industrial) and into mutually exclusive program categories (Retrofit and New Construction).

5. Interactive effects between measures

As discussed in question 1 above, all Investor Owned Utilities are directed to use DEER savings estimates to determine peak kW and kilowatt hour (kWh) program savings. Interactive effects are captured in DEER savings estimates.

6. List any studies or sources relied on

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[2] http://www.calmac.org/

[3] Page 39 OP 4

Data for the years 2000 to 2012 are based on SCE's Demand-Side Management, Energy Efficiency and Low Income Energy Efficiency Annual Reports.

SCE 2013-2014 program energy and demand impacts are based on SCE 2013-2014 program plans.[4] These impacts are subject to change as program plans are finalized.

Uncommitted data for years 2015-2020 are based on the Total Market Gross (TMG) goals, as required in CPUC Decision 08-07-047[5].

Data for year 2021 and 2024 were calculated using the compound annual growth rate for relevant TMG categories for years 2015-2020.

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[4] Compliance Advice Letter (AL 2838-E), pending CPUC approval

[5] Page 39 OP 3

Form 5 Committed Demand-Side Program Methodology
Demand Response Program Costs and Impacts

SCE's committed Demand Response estimates reflect actual historical data based on the reports on Interruptible Load Programs and Demand Response Programs. SCE is required, on a monthly basis, to submit MW load reductions for each interruptible load program and demand response program. The ex-ante MW represents the load reduction that SCE reasonably expects to obtain during a demand response event based on the historical compliance or performance of each program.

For Demand Response resources that have numerous events, regression analysis can be used to estimate the typical (absolute or percentage) load reduction associated with events as a function of event-day conditions (e.g., weather, day-of-week, etc.). These regression models can then be used to predict either ex ante or ex post impacts as a function of the conditions that occurred on those historical days or that are expected to occur on future days in which program events are most likely to be called.

<u>Base Interruptible Program (BIP)</u>

BIP is a year round reliability-based program available to customers with demand of 200 kW or greater that pays enrolled customers an incentive to reduce their facility's load to, or below, a level that is pre-determined by the customer when CAISO issues a curtailment notice. Customers choose a participation option, which is the amount of time (15 or 30 minutes) required for the customer to respond to a BIP event. Customers commit to reduce at least 15% of their maximum demand with a minimum of 100 kW during events.

1. Describe how the estimates of peak impacts for each program are derived.

The 2000-2009 adjusted MW reflects a composite program average performance for the most recent events, based on a comparison of the average kW demand exceeding the aggregate program Firm Service Level, to the Enrolled MW that month. The average rate was 97.3%. The Adjusted MW is equal to the compliance rate times the Enrolled MW.

The 2010-2014 program impacts are based on CPUC adopted Load Impact Protocols. Individual load patterns were modeled using historical hourly data for all participants with available data. Ex ante impacts were estimated as the reference load under 1-in-2 and 1-in-10 system peak conditions minus the firm service level, with adjustments based on historical over and under performance.

2. Describe assumptions about eligible population, participation rates, price elasticity, wholesale market conditions, and prices used to develop the projections.

Committed program load impacts are based on historical data. No projections were developed.

3. For dispatchable programs, describe what criteria will be used in deciding whether to dispatch and how they will be operated to reduce the peak.

See [Program Triggering Criteria Summary Table.]

Summer Discount Plan (SDP)

The SDP offers credit to customers who allow their air conditioning units to cycle off and on during curtailment events. SDP, previously known as The Air Conditioner Cycling Program (ACCP), was created in 1977 via Advice Letter 441-E and allows SCE to install a remote-controlled device on participating customers' central air conditioner outdoor compressor units. During curtailment events, participating customers' AC compressors are remotely cycled off and on, as necessary, to control the unit's load. In return for participating in the SDP program, customers receive a credit on their electric bills each year from the first of June to the first of October.

1. Describe how the estimates of peak impacts for each program are derived.

The 2000-2009 adjusted MW are based on historical impact studies. Estimates were calibrated to actual tonnage and super-hot day temperatures (>100 deg) at selected SCE locations, with correlated temperatures in other SCE weather zones.

The 2010-2014 program impacts are based on CPUC adopted Load Impact Protocols. For SDP-RES, events were dispatched at the A-bank level, so all customers associated with a given A-bank experienced the same events. For this reason, and also due to the large number of residential SDP participants, our evaluation approach involves averaging the customer-level load data by cycling strategy for each A-bank, and estimating average-customer load impact regression models. Program-level load impacts (for the portion of SDP customers for whom SmartConnect data were available) during a specific event-hour are constructed by combining load impacts for the appropriate A-banks and cycling strategies. These values, at the A-bank level, are scaled by the ratio of enrolled customers to customers with data to produce the final program values.

For SDP-COM, reference loads were developed from regression analysis applied to air conditioner end-use loads of a sample of commercial customers and simulated under the 1-in-2 and 1-in-10 weather scenarios. Percentage load impacts based on SDG&E's Summer Saver program were applied to the reference loads for each scenario to produce all of the required reference loads, estimated event-day loads, and scenarios of load impacts.

2. Describe assumptions about eligible population, participation rates, price elasticities, wholesale market conditions, and prices used to develop the projections.

Committed program load impacts are based on historical data. No projections were developed.

3. For dispatchable programs, describe what criteria will be used in deciding whether to dispatch and how they will be operated to reduce the peak.

See [Program Triggering Criteria Summary Table.]

Capacity Bidding Program

The CBP is a statewide price-responsive program that offers participants monthly incentives to reduce load to a pre-determined amount. This program was developed in 2006 as the successor to the California Power Authority Demand Reserves Partnership (CPA-DRP) program that terminated May 2007. CBP provides its participants (directly enrolled customers or aggregators) monthly capacity payments based on the amount of load reduction nominated per product or number of hours per event for each month, plus additional energy payments based on the kilowatt hour (kWh) reduction when an event is called. Participants can adjust their MW nomination each month, select an hourly product, and choose to participate in either a day-ahead or day-of option. CBP is open to bundled service and Direct Access customers with adequate metering.

1. Describe how the estimates of peak impacts for each program are derived.

The 2000-2009 adjusted MW are based on monthly nominations. For November through April the highest sum of nominations from the summer is reported.

The 2010-2014 program impacts are based on CPUC adopted Load Impact Protocols. Direct estimates of total program-level ex post load impacts for each program were developed from the coefficients of individual customer regression equations. These equations were estimated over the summer months using historical individual data for each customer account enrolled in each program. The ex ante estimates factored in historical event performance for each customer enrolled in the program at the end of the 2012 cycle.

2. Describe assumptions about eligible population, participation rates, price elasticity, wholesale market conditions, and prices used to develop the projections.

Committed program load impacts are based on historical data. No projections were developed.

3. For dispatchable programs, describe what criteria will be used in deciding whether to dispatch and how they will be operated to reduce the peak.

See Program Triggering Criteria Summary Table.

Agricultural and Pumping Interruptible Program

The Agricultural and Pumping Interruptible (AP-I) program provides a monthly credit to eligible agricultural and pumping customers for allowing SCE to temporarily interrupt electric service to their pumping equipment during CAISO or other system emergencies. Agricultural and pumping customers with a measured demand of 37 kW or greater, or with at least 50 horsepower of connected load per service account, are eligible to participate in the AP-I program.

When an interruption is deemed necessary and is allowed under the terms of the tariff, SCE sends a signal to the load control device installed on a customer's pumping equipment. The signal automatically turns off the equipment for the entire duration of the interruption event. AP-I customers can request to receive courtesy notifications of the start and end time of an interruption through means of email, pager and/or text message to a cell phone.

1. Describe how the estimates of peak impacts for each program are derived.

The 2000-2009 adjusted MW are based on actual monthly on-peak demand during the summer reporting months. Average of last summer's on-peak demands reported during winter months.

The 2010-2014 program impacts are based on CPUC adopted Load Impact Protocols. Agricultural pump loads were modeled as a function of time of day, day of week, rate periods, rainfall in prior weeks, temperature and other factors. Estimates of switch activation success rates were developed based on the historical test events and applied to reference loads.

2. Describe assumptions about eligible population, participation rates, price elasticities, wholesale market conditions, and prices used to develop the projections.

Committed program load impacts are based on historical data. No projections were developed.

3. For dispatchable programs, describe what criteria will be used in deciding whether to dispatch and how they will be operated to reduce the peak.

See Program Triggering Criteria Summary Table.

<u>Real Time Pricing Program</u>

The Real Time Pricing (Schedule RTP-2 or RTP) program is a dynamic pricing tariff that charges participants for the electricity they consume based on hourly prices that vary according to day type and temperature. It attempts to incorporate both the time-varying components of energy costs and generation capacity costs. The RTP tariff consists of nine hourly pricing profiles that vary by season, day type and a range of temperatures measured at the Downtown Los Angeles site on the previous day (see Figure 3-1). The tariff is available to large commercial and industrial customers (i.e., customers eligible for service under Schedule TOU-8).

1. Describe how the estimates of peak impacts for each program are derived.

The 2000-2009 adjusted MW are estimated based on 2007 data comparing load reductions on an extremely hot day to load reductions on a mild day.

The 2010-2014 program impacts are based on CPUC adopted Load Impact Protocols. Customer load was modeled as a function of time of day, day of week, weather, and hourly price schedules using historical hourly data. The impacts were estimated as the difference between customer loads under RTP and estimated hourly loads under the otherwise applicable tariff prices based on individual customer price response.

2. Describe assumptions about eligible population, participation rates, price elasticity, wholesale market conditions, and prices used to develop the projections.

Committed program load impacts are based on historical data. No projections were developed.

3. Describe the method used to develop estimates of non-dispatchable program impacts and the extent to which the forecast is consistent with recent program performance.

See Program Triggering Criteria Summary Table.

Demand Bidding Program

The DBP is a year-round internet-based bidding program that offers qualified participants the opportunity to receive bill credits for voluntarily reducing load when a DBP event is called. The program was established in 2003 to provide customers increased flexibility to participate in DR programs without incurring penalties. DBP is open to bundled service and Direct Access customers who have a demand of 200 kW or greater. Customers with service accounts that have demand between 50 and 199 kW can participate through aggregation if they have adequate metering and at least one service account with a registered demand of 200 kW or greater.

1. Describe how the estimates of peak impacts for each program are derived.

The 2000-2009 adjusted MW are based on performance percentage (highest single hourly reduction during summer event divided by annual max demand of enrolled customers) applied to current enrolled customers.

The 2010-2014 program impacts are based on CPUC adopted Load Impact Protocols. The ex post hourly load impacts were estimated using regression equations applied to customer-level hourly load data. Ex ante load impacts were estimated using percentage load impacts directly calculated from the ex post results and applied to 1-in-2 and 1-in-10 reference loads. Program-level load impacts are significantly higher than portfolio-level load impacts in all forecast years due to dual enrollment in BIP.

2. Describe assumptions about eligible population, participation rates, price elasticities, wholesale market conditions, and prices used to develop the projections.

Committed program load impacts are based on historical data. No projections were developed.

3. For dispatchable programs, describe what criteria will be used in deciding whether to dispatch and how they will be operated to reduce the peak.

See Program Triggering Criteria Summary Table.

Critical Peak Pricing

Critical Peak Pricing is an electric rate in which a utility charges a higher price for consumption of electricity during peak hours on selected days, referred to as critical peak days or event days. Typically, CPP hours coincide with the utility's peak demand and CPP days are called 5 to 15 times a year when demand is high and supply is short. The higher price during peak hours on critical event days is designed to encourage reductions in demand and reflects the fact that electric demand during those hours drives a substantial portion of electric infrastructure costs.

In 2009, the California Public Utilities Commission (CPUC) issued rate design guidance for dynamic pricing tariffs, such as CPP (CPUC decision (D.) 10-02-032). The decision standardized several key elements of dynamic pricing rate design for California IOUs:

- The default tariff for large and medium commercial and industrial customers must be a dynamic pricing tariff;

- Default rates must include a high price during peak periods on a limited number of critical event days and time of use rates on non-event days;

- The opt-out tariff for all non-residential default customers should be a time varying rate – in other words, there should no longer be a flat rate option for non-residential customers once the default schedule is completed;

- The critical peak price should represent the cost of capacity required to meet peak energy needs plus the marginal cost of energy – in essence, all capacity value should be allocated to peak period hours on critical event days; and

- Utilities should offer first year bill protection to customers defaulted onto dynamic rates.

1. Describe how the estimates of peak impacts for each program are derived.

The 2000-2009 adjusted MW are based on 15% of customer's annual max demand.

The 2010-2014 program impacts are based on CPUC adopted Load Impact Protocols. The CPP ex post hourly load impacts were estimated using difference-in-differences panel regression based on historical customer load data. The difference-in-differences approach produces more accurate results for individual CPP days when tested side-by-side with individual customer regressions. Put differently, the difference-in-differences method produces individual event day results that are less noisy, but the average impacts across all days are quite similar for the two methods. In the ex ante analysis, load impacts and the estimated reference load were based on the regression coefficients from the ex post model. The ex ante estimates factored in historical event performance for each customer enrolled in the program at the end of the 2012 cycle.

2. Describe assumptions about eligible population, participation rates, price elasticities, wholesale market conditions, and prices used to develop the projections.

Committed program load impacts are based on historical data. No projections were developed.

3. For dispatchable programs, describe what criteria will be used in deciding whether to dispatch and how they will be operated to reduce the peak.

See Program Triggering Criteria Summary Table.

Demand Response Contracts

The DRC program refers to contracts between SCE and third-party demand response contractors who develop their own demand response programs and provide load reductions to SCE. Customers enter into individual contractual arrangements with third-party DR contractors, and are compensated by the third-party DR contractor under the terms of their agreement.

1. Describe how the estimates of peak impacts for each program are derived.

The 2000-2009 adjusted MW are based on monthly nominations of contract capacity.

The 2010-2014 program impacts are based on CPUC adopted Load Impact Protocols. Direct estimates of total program-level ex post load impacts for each program were developed from the coefficients of individual customer regression equations. These equations were estimated over the summer months using historical individual data for each customer account enrolled in each program. The ex-ante estimates factored in historical event performance for each customer enrolled in the program at the end of the 2012 cycle.

2. Describe assumptions about eligible population, participation rates, price elasticities, wholesale market conditions, and prices used to develop the projections.

Committed program load impacts are based on historical data. No projections were developed.

3. For dispatchable programs, describe what criteria will be used in deciding whether to dispatch and how they will be operated to reduce the peak.

See Program Triggering Criteria Summary Table.

Save Power Day (SPD)

SCE's Save Power Day (PTR) program includes the following features:
Two rebate levels are available—a basic level of $0.75/kWh and a premium level of $1.25/kWh for customers who use automated enabling technology installed through an SCE program.
Load reductions for rebate purposes are measured relative to a customer-specific reference level (CRL) based on an average of the highest 3 out of the most recent 5 similar non-event days.[6]
The number of events in a typical year may range from twelve to fifteen, usually during the summer, and always on weekdays, with an event window of 2 p.m. to 6 p.m. SCE called seven events in 2012 as the smart meters were still being deployed.

1. Describe how the estimates of peak impacts for each program are derived.

The 2000-2012 MW are based on the SmartConnect mid-level model utilizing the price elasticities from the Statewide Pricing Pilot (SPP) modeling various input assumptions, including the participation rate, event awareness, price elasticities, and rebate amount.
The 2013-2014 program impacts are based on CPUC adopted Load Impact Protocols. The evaluation approach began with the design and selection of a sample of customers from the approximately 400,000 customers who were enrolled to receive electronic notification of PTR events as of the second event, on August 10. Hourly load data for the sampled customers, who were stratified by climate zone and size (usage level), were then aggregated into four groups defined by climate zone (Coastal and Inland) and type of notification (default and opt-in). Load-impact regression models were estimated for each group, after a process of testing and validating alternative models, including appropriate weather variables. In parallel, load data for all of the SDP participants were aggregated into three groups based on type of notification (default, opt-in, and no notice), and regression models were estimated for each group, producing estimates of hourly load impacts for each PTR event.

2. Describe assumptions about eligible population, participation rates, price elasticities, wholesale market conditions, and prices used to develop the projections.

Committed program load impacts are based on historical data. No projections were developed.

3. For dispatchable programs, describe what criteria will be used in deciding whether to dispatch and how they will be operated to reduce the peak.

See Program Triggering Criteria Summary Table.

Program Triggering Criteria Summary Table

Program	Type	Program Season	Available Annual Events/Hours	Available Monthly Events/Hours	Available Weekly Events/Hours	Available Daily Events/Hours	Available Trigger Criteria
Agricultural Pumping Interruptible (API)	Day Of	Year Round (excluding Holidays)	150 Hours	25 Events	4 Events	1 Event 6 Hours Max	• CAISO Stage 1 Alert • CAISO Stage 2 Alert • SCE Grid Control Center Discretion • Measurement & Evaluation
Base Interruptible Program (BIP)	Day Of	Year Round (excluding Holidays)	180 Hours	10 Events	No Limit	1 Event 6 Hours Max	• CAISO Stage 1 Alert • CAISO Stage 2 Alert • SCE Grid Control Center Discretion • Measurement & Evaluation
Capacity Bidding Program (CBP-DA)	Day Ahead	May – Oct (excluding Holidays)	No Limit	24 Hours	Mon-Fri	1 Event 8 Hours (11am – 7pm)	• High temperature • Resource limitations • A generating unit outage • Transmission constraints • CAISO Alert or Warning • SCE System Emergency • Measurement & Evaluation

Capacity Bidding Program (CBP-DO)	Day Of	May – Oct (excluding Holidays)	No Limit	24 Hours	No Limit	1 Event 4,6, or 8 hour event duration options	• High temperature • Resource limitations • A generating unit outage • Transmission constraints • CAISO Alert or Warning • SCE System Emergency • Measurement & Evaluation
Demand Bidding Program (DBP)	Day Ahead	Year Round (excluding Holidays)	No Limit	No	No Limit Mon-Fri	1 Event 8 hours	• CAISO Alert or Warning • Day-Ahead load and/or Price Forecast • Extreme or unusual temperature conditions • SCE Procurement needs • Measurement & Evaluation
DR Contracts (DRC-DA)	Day Ahead	Varies	Varies by Contract	Varies by Contract	Varies by Contract	Varies by Contract	Varies by Contract
DR Contracts (DRC-DO)	Day Of	Varies	Varies by Contract	Varies by Contract	Varies by Contract	Varies by Contract	Varies by Contract
Save Power Day (SPD)	Day Ahead	Year Round (excluding Holidays)	No Limit	No Limit	No Limit	1 Event 4 Hours (2pm – 6pm)	• Temperature

Summer Advantage Incentive (SAI)	Day Of	June – Sep (excluding Holidays)	60 Hours Min: 9 Events Max: 15 Events	No Limit	No Limit	1 Event 4 Hours (2pm – 6pm)	• Temperature • CAISO Alert or Warning • SCE System Forecast • Extreme or unusual temperature conditions • Day-Ahead load and/or Price Forecast
Summer Discount Plan - Residential (SDP-RES)	Day Of	Year Round (excluding Holidays)	Unlimited Events 180 Hours	No Limit	No Limit	Unlimited Events 6 Hours	• CAISO Alert or Warning • CAISO Discretion • SCE Grid Control Center Discretion • SCE Energy Operations Center Discretion • Measurement & Evaluation
Summer Discount Plan – Commercial (SDP-COM)	Day Of	Year Round (excluding Holidays)	Base – 90 Hours Enhanced – Unlimited	No Limit	No Limit	6 Hours	• CAISO Stage 1 Alert • CAISO Stage 2 Alert • SCE Grid Control Center Discretion • Measurement & Evaluation

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Renewable and Distributed Generation Program Costs and Impacts

Data Sources

SCE's forecast of self-generation is developed from a list of customers operating or planning to operate generating systems interconnected to the grid for the purpose of meeting their own energy requirements. This list of customers includes self-generation projects at various stages of development, including:

- systems on-line,
- systems under construction,
- systems currently being planned for installation

The description of each self-generation project includes customer description, nameplate capacity in kilowatts (kW), probable bypass kW, capacity factor, and on-line date. The list provides both estimated bypass capacity and estimated annual energy. SCE draws from multiple internal databases in an effort to make its list of customer self-generation projects as exhaustive as possible, including SCE's customer account data, customer generation project tracking system, and Rule 21 requests for interconnection. These databases contain data regarding DG (thermal generation) customers and NEM (solar/renewable) customers.

SCE develops separate forecasts for thermal and solar/renewable systems. The methodologies used to develop each of these forecasts are described further below. These forecasts are ultimately combined for use in SCE's sales forecast.

Forecasting Methodology

Thermal Generation

Effective January 1, 2012, Assembly Bill 1150 reaffirms that the California Public Utilities Commission shall require administration of the SGIP until January 1, 2016. Given the uncertainty of the SGIP, SCE has reported the forecasted impacts of thermal generation as uncommitted from 2016-2024 SCE is assuming an additional 11 MW of thermal generation per year after that time period with the exception of one year where SCE knows of an additional probable unit.

Solar/Renewal Generation

Decision D.06-01-024 allocated funding for CSI through 2016. Given that the future of the program is uncertain after 2016, SCE has reported the forecasted impacts of solar/renewable generation as uncommitted from 2017 – 2024.

Based on recent trends and current interconnection requests by customers, approximately 98MW to 51MW of Renewable customer generation per year are added to the forecast for the period 2017 – 2024. This forecast maintains the trend of the committed solar/renewable forecast, but re-characterizes the impacts from committed to uncommitted based on the uncertain future of the CSI Program after 2016.

Form 6 Uncommitted Demand-Side Program Methodology
Energy Efficiency Program Impacts

SCE has classified Energy Efficiency (EE) program results 2000-2012 as historical, 2013-2014 as committed, and 2015-2024 as program results as uncommitted.

1. Describe how the peak and energy impacts are calculated

From 2000 through 2005, SCE utilized California IOU Database for Energy Efficiency Resources (DEER) values, Evaluation Measurement and Verification (EM&V) studies, and/or engineering work papers to estimate EE impacts and costs by measure.

In Decision 06-06-063 (June 29, 2006) the California Public Utilities Commission (CPUC) directed all California investor owned utilities to:

a) Use the Database for Energy Efficient Resources (DEER) values for peak kW and kilowatt hour (kWh) savings for those measures that are included in the DEER database.

b) Continue to use their best estimates of those values for measures that are not currently included in DEER, or for programs with measure categories rather than specific measures, such as customized rebate programs.

c) Use the following definition of peak demand savings:
The average grid level impact for a measure between 2 p.m. and 5 p.m. during the three consecutive weekday period containing the weekday temperature with the hottest temperature of the year.

Since 2006, SCE has used the DEER peak demand reduction and annual energy savings estimates as its primary resource for energy efficiency program savings. For measures not found in DEER, detailed work papers documenting savings estimates are utilized. Note that SCE also documents in work papers measure values that are derived through averaging DEER values.

2. Describe the basis or method used to estimate how first-year impacts might change over time

The 2000-2009 historic peak and energy impact data were extracted from SCE's Annual DSM reports, Annual Energy Efficiency reports and/or CPUC Energy Efficiency Quarterly Reports.

SCE's reported peak and energy impacts are primarily *ex-ante* engineering estimates, whether the source is the DEER or SCE work papers. For the committed period, SCE relies upon DEER and/or SCE work papers; however, the final *ex-ante* assumptions are pending final approval by the CPUC.

3. Document the net-to-gross ratios used to convert gross measure or program impacts into net impacts

EE results for 2000-2008 were reported as net impacts, and then converted to Gross energy/demand impacts using the individual program net-to-gross ratios (NTGRs) contained in the CPUC Energy Efficiency Policy Manual.

Over the course of a program cycle, some of the NTGRs were updated based on the results of the final energy efficiency EM&V impact evaluations, which can be found on the CALMAC[1] website.

EE results reported for 2009-2012 and 2013-2014 proposed EE program impacts (2838E) are gross impacts per the California Public Utilities Commission (CPUC) Decision 08-07-047[2]. Gross impacts were converted to net impacts utilizing the NTGRs contained in the CPUC maintained and approved DEER database.

4. Describe how the per-measure impact estimates are aggregated and how interactive effects between the measures are estimated or accounted for

SCE interpreted this question to be asking how measure level data was aggregated to the sector and program categories.

SCE deployed a bottom up methodology designed to aggregate EE impacts and costs to the sector and program level. SCE started by determining the energy/demand and costs measure level impacts (described in question 1 above). To calculate the sector and program measure level impacts, the per measure savings estimates (energy, demand and costs) were multiplied by the number of measure installations attributable to a mutually exclusive program and sector in a given year.

SIC/NAICS codes were used to allocate EE savings to the sector level where crosscutting EE programs and measures transcended multiple sectors. By using SIC/NAICS codes, SCE was able to allocate energy/demand savings and costs into mutually exclusive sector grouping (Residential, Commercial, and Industrial) and into mutually exclusive program categories (Retrofit and New Construction).

5. Interactive effects between measures

As discussed in question 1 above, all Investor Owned Utilities are directed to use DEER savings estimates to determine peak kW and kilowatt hour (kWh) program savings. Interactive effects are captured in DEER savings estimates.

6. List any studies or sources relied on

[1] http://www.calmac.org/

[2] Page 39 OP 4

Data for the years 2000 to 2012 are based on SCE's Demand-Side Management, Energy Efficiency and Low Income Energy Efficiency Annual Reports.

SCE 2013-2014 program energy and demand impacts are based on SCE 2013-2014 program plans[3]. These impacts are subject to change as actual program plans are finalized.

Uncommitted data for years 2015-2020 are based on the Total Market Gross (TMG) goals, as required in CPUC Decision 08-07-047[4].

Data for year 2021 and 2024 were calculated using the compound annual growth rate for relevant TMG categories for years 2015-2020.

7. Discuss the current status of programs included in the uncommitted forecast.

SCE's 2013-2014 EE portfolio is very comprehensive, and includes far reaching programs/measures from the California EE Strategic Plan, Emerging Technologies, and other programs that have not historically included in SCE's EE portfolio. Program examples include:

- Energy Upgrade California (Whole Home Upgrade) -
  - Targets single family homes and is designed to promote deeper more comprehensive energy savings
- Behavioral EE
  - Designed to help customer change behaviors and reduce energy use
- On Bill Financing/Repayment
  - Designed increase EE program adoption by removing barriers to EE program adoption. This program finances EE retrofits and allow repayment through the energy billing process.
- Code and Standard
  - Provides support for new code and standard adoptions
- Emerging Technologies
  - Designed to introduce and advocate customer adoption of new technologies
- Water/Energy Nexus
  - This pilot program helps customers save water and thus have the energy required to transport water to the customer location
- New Construction
  - Designed to help customers achieve California's EE Strategic Plan's goal of zero net energy use for newly construction residential and commercial buildings
- IDEA 365

[3] Compliance Advice Letter (AL 2838-E), pending CPUC approval

[4] Page 39 OP 3

    - Solicits new energy saving program ideas and integrates select ideas into SCE’s EE portfolio
- Partnerships
    - SCE partners with cities and counties to provide additional channels for customer adoption of EE programs

Working with the CPUC and other Stakeholders, it is anticipated that SCE programs will continue to introduce SCE customers to cutting edge EE programs and services over time, and thus keep California leading the way in helping customer save electricity and the environment.

Form 6 Uncommitted Demand-Side Program Methodology
Demand Response Program Costs and Impacts

Describe how the estimates of peak impacts for each program are derived.

SCE's uncommitted Demand Response forecast reflects ex-ante estimates based on the Load Impact Protocols[5]. The protocols governing the development of ex-ante load impacts were designed to help ensure that demand response impact estimates would be directly comparable with other resource alternatives (i.e., other DR resources, energy efficiency, renewables, and generation). The protocols require that the ex-ante load impact estimates be based on analysis of historical data whenever the existing data and characteristics of the program allow for such an approach. Analysis of historical program data is then employed to produce ex-ante load impact estimates that are subsequently used for resource adequacy, cost-effectiveness assessment and, by connection, resource planning.

Ex-ante load impacts reflect the fact that demand response load impacts vary as a function of weather, participant characteristics, changes in the number of program participants and other factors such as switch failure rates in order to provide an appropriate comparison with alternative resources under the same planning paradigm. Put differently, ex-post load impacts for any given year may differ from the load impacts that could be achieved during the low probability, extreme conditions under which many DR resources are likely to be used and for which they provide insurance value.

For dispatchable programs, describe what criteria will be used in deciding whether to dispatch and how they will be operated to reduce the peak.

See Program Triggering Criteria Summary Table.

Describe the process that will lead to change in status from uncommitted to committed, and whether this change is under the control of the LSE or imposed through regulatory requirements.

The demand response programs will change from uncommitted to committed once the CPUC adopts a final decision on the IOUs' demand response activity and budget applications. The next three year demand response activity and budget cycle is 2015-2017.

Base Interruptible Program (BIP)

BIP is a year round reliability-based program available to customers with demand of 200 kW or greater that pays enrolled customers an incentive to reduce their facility's load to, or below, a level that is pre-determined by the customer when CAISO issues a curtailment notice. Customers choose a participation option, which is the amount of time (15 or 30 minutes) required for the

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[5] D.08-04-050, Attachment A, *Load Impact Estimation for Demand Response: Protocols and Regulatory Guidance,* California Public Utilities Commission, Energy Division, April 2008 (the Load Impact Protocols).

customer to respond to a BIP event. Customers commit to reduce at least 15% of their maximum demand with a minimum of 100 kW during events.

Describe assumptions about eligible population, participation rates, price elasticities, wholesale market conditions, and prices used to develop the projections.

Individual load patterns were modeled using historical hourly data for all participants with available data. Ex ante impacts were estimated as the reference load under 1-in-2 and 1-in-10 system peak conditions minus the firm service level, with adjustments based on historical over and under performance.

SCE projects that BIP enrollment will remain constant throughout the ex-ante uncommitted forecast period. Although enrollment does not change, ex-ante load impact estimates increase slightly over time due to load growth.

Summer Discount Plan (SDP)

The SDP currently a reliability-based program, is now requested to be transitioned to a price-responsive program that offers credit to customers who allow their air conditioning units to cycle off and on during curtailment events. SDP, previously known as The Air Conditioner Cycling Program (ACCP), was created in 1977 via Advice Letter 441-E and allows SCE to install a remote-controlled device on participating customers' central air conditioner outdoor compressor units. During curtailment events, participating customers' AC compressors are remotely cycled off and on, as necessary, to control the unit's load. In return for participating in the SDP program, customers receive a credit on their electric bills each year from the first of June to the first of October.

Describe assumptions about eligible population, participation rates, price elasticities, wholesale market conditions, and prices used to develop the projections.

For SDP-RES, events were dispatched at the A-bank level, so all customers associated with a given A-bank experienced the same events. For this reason, and also due to the large number of residential SDP participants, our evaluation approach involves averaging the customer-level load data by cycling strategy for each A-bank, and estimating average-customer load impact regression models. Program-level load impacts (for the portion of SDP customers for whom SmartConnect data were available) during a specific event-hour are constructed by combining load impacts for the appropriate A-banks and cycling strategies. These values, at the A-bank level, are scaled by the ratio of enrolled customers to customers with data to produce the final program values. SCE assumes a 1.4 percent increase in SDP-RES enrollments in 2015 and then to remain constant from 2015 through 2023.

For SDP-COM, reference loads were developed from regression analysis applied to air conditioner end-use loads of a sample of commercial customers and simulated under the 1-in-2 and 1-in-10 weather scenarios. Percentage load impacts based on SDG&E's Summer Saver program were applied to the reference loads for each scenario to produce all of the required reference loads, estimated event-day loads, and scenarios of load impacts.

Capacity Bidding Program (CBP)

The CBP is a statewide price-responsive program that offers participants monthly incentives to reduce load to a pre-determined amount. This program was developed in 2006 as the successor to the California Power Authority Demand Reserves Partnership (CPA-DRP) program that terminated May 2007. CBP provides its participants (directly enrolled customers or aggregators) monthly capacity payments based on the amount of load reduction nominated per product or number of hours per event for each month, plus additional energy payments based on the kilowatt hour (kWh) reduction when an event is called. Participants can adjust their MW nomination each month, select an hourly product, and choose to participate in either a day-ahead or day-of option. CBP is open to bundled service and Direct Access customers with adequate metering.

Describe assumptions about eligible population, participation rates, price elasticities, wholesale market conditions, and prices used to develop the projections.

Direct estimates of total program-level ex post load impacts for each program were developed from the coefficients of individual customer regression equations. These equations were estimated over the summer months using historical individual data for each customer account enrolled in each program. The ex-ante estimates factored in historical event performance for each customer enrolled in the program at the end of the 2012 cycle. Day-ahead nominations are expected to remain small, while day-Of nominations are anticipated to fall over the forecast horizon due to aggregators moving customers from CBP to DRC.

Agricultural and Pumping Interruptible Program (AP-I)

The Agricultural and Pumping Interruptible (AP-I) program provides a monthly credit to eligible agricultural and pumping customers for allowing SCE to temporarily interrupt electric service to their pumping equipment during CAISO or other system emergencies. Agricultural and pumping customers with a measured demand of 37 kW or greater, or with at least 50 horsepower of connected load per service account, are eligible to participate in the AP-I program.

When an interruption is deemed necessary and is allowed under the terms of the tariff, SCE sends a signal to the load control device installed on a customer's pumping equipment. The signal automatically turns off the equipment for the entire duration of the interruption event. AP-I customers can request to receive courtesy notifications of the start and end time of an interruption through means of email, pager and/or text message to a cell phone.

Describe assumptions about eligible population, participation rates, price elasticities, wholesale market conditions, and prices used to develop the projections.

Agricultural pump loads were modeled as a function of time of day, day of week, rate periods, rainfall in prior weeks, temperature and other factors. Estimates of switch activation success rates were developed based on the historical test events and applied to reference loads. Although

SCE is not actively marketing this program, it's expected to experience continued enrollment growth over the next few years.

Real Time Pricing Program (RTP)

The Real Time Pricing (Schedule RTP-2 or RTP) program is a dynamic pricing tariff that charges participants for the electricity they consume based on hourly prices that vary according to day type and temperature. It attempts to incorporate both the time-varying components of energy costs and generation capacity costs. The RTP tariff consists of nine hourly pricing profiles that vary by season, day type, and a range of temperatures measured at the Downtown Los Angeles site on the previous day (see Figure 3-1). The tariff is available to large commercial and industrial customers (i.e., customers eligible for service under Schedule TOU-8). Enrollment is expected to remain relatively constant throughout the forecast horizon.

Describe assumptions about eligible population, participation rates, price elasticities, wholesale market conditions, and prices used to develop the projections.

Customer load was modeled as a function of time of day, day of week, weather, and hourly price schedules using historical hourly data. The impacts were estimated as the difference between customer loads under RTP and estimated hourly loads under the otherwise applicable tariff prices based on individual customer price response.

Demand Bidding Program (DBP)

The DBP is a year-round internet-based bidding program that offers qualified participants the opportunity to receive bill credits for voluntarily reducing load when a DBP event is called. The program was established in 2003 to provide customers increased flexibility to participate in DR programs without incurring penalties. DBP is open to bundled service and Direct Access customers who have a demand of 200 kW or greater. Customers with service accounts that have demand between 50 and 199 kW can participate through aggregation if they have adequate metering and at least one service account with a registered demand of 200 kW or greater.

Describe assumptions about eligible population, participation rates, price elasticities, wholesale market conditions, and prices used to develop the projections.

The ex post hourly load impacts were estimated using regression equations applied to customer-level hourly load data. Ex ante load impacts were estimated using percentage load impacts directly calculated from the ex post results and applied to 1-in-2 and 1-in-10 reference loads. Program-level load impacts are significantly higher than portfolio-level load impacts in all forecast years due to dual enrollment in BIP. SCE forecasts that DBP customer enrollment to decrease in 2014 due to the removal of "non-performing" customers (pending Resolution E-4563 approval), and then begin enrolling under-200kW customers in 2015.

Critical Peak Pricing (CPP)

Critical Peak Pricing is an electric rate in which a utility charges a higher price for consumption of electricity during peak hours on selected days, referred to as critical peak days or event days. Typically, CPP hours coincide with the utility's peak demand and CPP days are called 5 to 15 times a year when demand is high and supply is short. The higher price during peak hours on critical event days is designed to encourage reductions in demand and reflects the fact that electric demand during those hours drives a substantial portion of electric infrastructure costs.

In 2009, the California Public Utilities Commission (CPUC) issued rate design guidance for dynamic pricing tariffs, such as CPP (CPUC decision (D.) 10-02-032). The decision standardized several key elements of dynamic pricing rate design for California IOUs:

- The default tariff for large and medium commercial and industrial customers must be a dynamic pricing tariff;
- Default rates must include a high price during peak periods on a limited number of critical event days and time of use rates on non-event days;
- The opt-out tariff for all non-residential default customers should be a time varying rate – in other words, there should no longer be a flat rate option for non-residential customers once the default schedule is completed;
- The critical peak price should represent the cost of capacity required to meet peak energy needs plus the marginal cost of energy – in essence, all capacity value should be allocated to peak period hours on critical event days; and
- Utilities should offer first year bill protection to customers defaulted onto dynamic rates.

Describe assumptions about eligible population, participation rates, price elasticities, wholesale market conditions, and prices used to develop the projections.

The CPP ex post hourly load impacts were estimated using difference-in-differences panel regression based on historical customer load data. The difference-in-differences approach produces more accurate results for individual CPP days when tested side-by-side with individual customer regressions. Put differently, the difference-in-differences method produces individual event day results that are less noisy, but the average impacts across all days are quite similar for the two methods. In the ex ante analysis, load impacts and the estimated reference load were based on the regression coefficients from the ex post model. The ex ante estimates factored in historical event performance for each customer enrolled in the program at the end of the 2012 cycle. Enrollment is expected to remain relatively constant throughout the forecast horizon.

<u>Demand Response Contracts (DRC)</u>

The DRC program refers to contracts between SCE and third-party demand response contractors who develop their own demand response programs and provide load reductions to SCE. Customers enter into individual contractual arrangements with third-party DR contractors, and are compensated by the third-party DR contractor under the terms of their agreement.

Describe assumptions about eligible population, participation rates, price elasticities, wholesale market conditions, and prices used to develop the projections.

Direct estimates of total program-level ex post load impacts for each program were developed from the coefficients of individual customer regression equations. These equations were estimated over the summer months using historical individual data for each customer account enrolled in each program. The ex-ante estimates factored in historical event performance for each customer enrolled in the program at the end of the 2012 cycle.

Save Power Day (SPD)

SCE's Save Power Day (PTR) program includes the following features:
Two rebate levels are available—a basic level of $0.75/kWh and a premium level of $1.25/kWh for customers who use automated enabling technology installed through an SCE program.
Load reductions for rebate purposes are measured relative to a customer-specific reference level (CRL) based on an average of the highest 3 out of the most recent 5 similar non-event days.[6]
The number of events in a typical year may range from twelve to fifteen, usually during the summer, and always on weekdays, with an event window of 2 p.m. to 6 p.m. SCE called seven events in 2012 as the smart meters were still being deployed.

Describe assumptions about eligible population, participation rates, price elasticities, wholesale market conditions, and prices used to develop the projections.

The evaluation approach began with the design and selection of a sample of customers from the approximately 400,000 customers who were enrolled to receive electronic notification of PTR events as of the second event, on August 10. Hourly load data for the sampled customers, who were stratified by climate zone and size (usage level), were then aggregated into four groups defined by climate zone (Coastal and Inland) and type of notification (default and opt-in). Load-impact regression models were estimated for each group, after a process of testing and validating alternative models, including appropriate weather variables. In parallel, load data for all of the SDP participants were aggregated into three groups based on type of notification (default, opt-in, and no notice), and regression models were estimated for each group, producing estimates of hourly load impacts for each PTR event.

Program Triggering Criteria Summary Table

Program	Type	Program Season	Available Annual Events/Hours	Available Monthly Events/Hours	Available Weekly Events/Hours	Available Daily Events/Hours	Available Trigger Criteria
Agricultural Pumping Interruptible (API)	Day Of	Year Round (excluding Holidays)	150 Hours	25 Events	4 Events	1 Event 6 Hours Max	• CAISO Stage 1 Alert • CAISO Stage 2 Alert • SCE Grid Control Center Discretion • Measurement & Evaluation
Base Interruptible Program (BIP)	Day Of	Year Round (excluding Holidays)	180 Hours	10 Events	No Limit	1 Event 6 Hours Max	• CAISO Stage 1 Alert • CAISO Stage 2 Alert • SCE Grid Control Center Discretion • Measurement & Evaluation
Capacity Bidding Program (CBP-DA)	Day Ahead	May – Oct (excluding Holidays)	No Limit	24 Hours	Mon-Fri	1 Event 8 Hours (11am – 7pm)	• High temperature • Resource limitations • A generating unit outage • Transmission constraints • CAISO Alert or Warning • SCE System Emergency • Measurement & Evaluation

Capacity Bidding Program (CBP-DO)	Day Of	May – Oct (excluding Holidays)	No Limit	24 Hours	No Limit	1 Event 4,6, or 8 hour event duration options	• High temperature • Resource limitations • A generating unit outage • Transmission constraints • CAISO Alert or Warning • SCE System Emergency • Measurement & Evaluation
Demand Bidding Program (DBP)	Day Ahead	Year Round (excluding Holidays)	No Limit	No	No Limit Mon-Fri	1 Event 8 hours	• CAISO Alert or Warning • Day-Ahead load and/or Price Forecast • Extreme or unusual temperature conditions • SCE Procurement needs • Measurement & Evaluation
DR Contracts (DRC-DA)	Day Ahead	Varies	Varies by Contract	Varies by Contract	Varies by Contract	Varies by Contract	Varies by Contract
DR Contracts (DRC-DO)	Day Of	Varies	Varies by Contract	Varies by Contract	Varies by Contract	Varies by Contract	Varies by Contract
Save Power Day (SPD)	Day Ahead	Year Round (excluding Holidays)	No Limit	No Limit	No Limit	1 Event 4 Hours (2pm – 6pm)	• Temperature

Summer Advantage Incentive (SAI)	Day Of	June – Sep (excluding Holidays)	60 Hours Min: 9 Events Max: 15 Events	No Limit	No Limit	1 Event 4 Hours (2pm – 6pm)	• Temperature • CAISO Alert or Warning • SCE System Forecast • Extreme or unusual temperature conditions • Day-Ahead load and/or Price Forecast
Summer Discount Plan - Residential (SDP-RES)	Day Of	Year Round (excluding Holidays)	Unlimited Events 180 Hours	No Limit	No Limit	Unlimited Events 6 Hours	• CAISO Alert or Warning • CAISO Discretion • SCE Grid Control Center Discretion • SCE Energy Operations Center Discretion • Measurement & Evaluation
Summer Discount Plan – Commercial (SDP-COM)	Day Of	Year Round (excluding Holidays)	Base – 90 Hours Enhanced – Unlimited	No Limit	No Limit	6 Hours	• CAISO Stage 1 Alert • CAISO Stage 2 Alert • SCE Grid Control Center Discretion • Measurement & Evaluation

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 income, 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

SCE assumed for the purposes of this forecast that a total allotment of 3,946 GWh will switch from SCE bundled service to a direct access ESP. The allotment is phased-in over a four year period, with 35 percent of the allotment occurring in 2010, another 35 percent in 2011, 20 percent in 2012 and the final 10 percent in 2013. DA sales from ‘existing’ customers (DA customers prior to the reopening of Direct Access in 2010) are assumed constant throughout the forecast period with the exception of small increases in sales caused by the introduction of PEV fleet charging and other sources of new electo-technology use.

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

SCE uses employment per customer or per square foot to explain how electricity consumption varies in response to changing economic conditions. It turns out that changes in employment are 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.

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 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 employment data by county is obtained from the California Economic Development Department. IHS Global Insight (HIS-GI) provides forecast employment data for California. The EDD historical data used is non-seasonally adjusted. The IHS-G I employment forecast data is converted from seasonally adjusted to non-seasonally adjusted. Because of a significant difference in the outlook for manufacturing employment in the SCE service area and California between IHS-GI and Moody's Analytics, we now use an average of the two manufacturing employment forecasts in our Industrial customer class electricity use econometric model. We plan to extend the averaging method to commercial services and government employment in future forecasts.

In future forecasts (starting with April 2013) we plan to extend the 'averaging' process to private commercial services employment and government employment, as there are also differences in outlooks between Moody's and HIS-GI that can best be resolved by an average of the respective forecasts

The short-run employment elasticity in the commercial customer class model is in the range of 0.6 to 0.7. The manufacturing employment elasticity is in the range of 0.5 to 0.6. The short-run government employment elasticity is estimated to be about 0.4 and the agriculture employment elasticity is about 0.9.

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-Ontario, 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 using an average unit revenue price with a one period lag (with the exception of the industrial and agriculture electricity consumption models, which do 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, the short-run residential elasticity, as derived from our forecast models, is generally in the range of -0.15 to -0.25. 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'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 energy efficiency (EE) program cycle. Committed EE is not distinguished from uncommitted EE in developing SCE's sales forecast.

For the 2013 ERRA, 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 2005 are based on SCE's Energy Efficiency Annual Reports ("May 1 Report). 2006-2011 are actual reported results. All historical numbers include SCE's Low Income Energy Efficiency (LIEE) Program. For consistency with Total Market Gross (TMG) SCE's Demand Forecasting group translates net savings from the historical time period into gross equivalent values to use in developing SCE's sales forecast.

SCE's energy efficiency forecast for 2012 is based on SCE's most current program plans[1]. Consistent with CPUC direction, savings impacts for SCE's Low Income Energy Efficiency (LIEE) Program are counted toward the EE goals.[2] As ordered in D.08-07-047, IOU EE goals for 2012 are gross, not net of free riders.[3]

For the period 2013 – 2014, SCE's energy efficiency forecast reflects the energy efficiency goals ordered in D.12-05-015. For the period 2015 – 2020, SCE's energy efficiency forecast reflects the Total Market Gross (TMG) energy efficiency goals ordered in D.08-07-047.[4] 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)

SCE's estimates of EE are aggregated upward from program level through 2012. 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.[5]

The monthly energy efficiency savings are estimated by distributing the annual savings using hourly load shapes based on the historical hourly energy data starting in 1998. 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. Pre 2006 program decay is based upon appliance life

[1] SCE compliance filing (2410-E), approved by Commission on April 8, 2010.
[2] D.04-09-060, FOF #13
[3] D.08-07-047, OP #4
[4] D.08-07-047, OP #1
[5] California Energy Efficiency Potential Study, Itron, Inc., 2008

calculations. Post 2006 program decay is assumed to be taken-up by future federal/state appliance and building standards and market transformation.

SCE has taken the position that EE should be explicitly included in the econometric estimation of kWh consumption per customer. As such, there are two possible ways to specify EE: 1) as an exogenous variable (i.e. on the right hand side of the equation) or as a component of consumption (i.e. on the left hand side of the equation where EE is treated as consumption that would have taken place in the absence of SCE programs). There are positives and negatives to both approaches. The main problem with the first approach is that the estimated coefficient on EE is likely to be different from one. If this is the case, then the sales forecast will not accurately reflect the savings that DSM planners have assumed. The second approach assumes implicitly that the EE coefficient is equal to one. Specifying EE as a component of the dependent variable adds an additional element of element of uncertainty to the econometric estimation that is not directly quantified. A third approach is to omit EE from econometric estimation altogether, but deduct it after the fact on an incremental basis. However, determining what EE is incremental to the forecast is difficult to determine since historical EE impacts are captured in the model coefficients. SCE believes that the second approach is the most direct and transparent method of incorporating EE impacts, both historical and forecast, into the forecast process.

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 2001 to 2007 period – a period of economic contraction and recovery, and the period 2008 to the present, which saw a sharp decline in real incomes due to high levels of unemployment and depressed real estate prices. Although changes in real income 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 per capita income elasticities are typically in range of 0.5 to 0.6. We use an average of historical and forecast real income per capita by county from Moody's and IHS-GI in our regional residential OLS forecasting models

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 700 operational thermal systems ranging in size from 1KW to 76 Megawatts (MW) within the SCE service area. Based on current programs and ongoing discussions for three large installations, 24 MW are added on average between 2013 and 2024.

There are approximately 41,000 operational solar systems ranging in size from 1KW to 1030 KW within the SCE service area. The forecast for 2013 includes solar facilities currently in the pipeline. The projection of solar bypass for 2013 includes solar facilities currently in the pipeline and targets set in the California Solar Initiative (CSI) and the 2013 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. Other components are zero net energy home construction, conservation induced by the presence of smart meter real time rate information and new regulations concerning the efficiency of lighting in homes and businesses.

3) Historic Forecast Performance

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

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

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

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

The definitions of RMSE and MAPE are as follows:

Suppose the forecast sample is j = T + 1, T + 2, …,T + *h*
Let $S_{F,t}$ represent predicted sales in period t and $S_{N,t}$ represent actual adjusted sales in period t; then:

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

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

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

An analysis of the 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 2012

	Actual (Weather Adj.) (MWh)	Forecast Oct 2011 Vintage (MWh)	MAPE Calculation
Jan-12	7,206,609	7,277,022	0.0098
Feb-12	6,028,832	5,993,800	0.0058
Mar-12	6,773,870	6,813,990	0.0059
Apr-12	6,255,618	6,269,818	0.0023
May-12	6,445,212	6,492,950	0.0074
Jun-12	7,172,156	7,229,054	0.0079
Jul-12	7,684,874	7,645,610	0.0051
Aug-12	8,332,799	8,138,528	0.0233
Sep-12	7,560,191	7,946,373	0.0511
Oct-12	7,020,143	7,477,188	0.0651
Nov-12	6,810,682	6,838,080	0.0040
Dec-12	7,196,823	7,026,586	0.0237
Jan-Aug Total (GWh)	55,900	55,861	0.8%
Jan-Dec Total (GWh)	84,488	85,149	1.8%
Simple Error- Jan-Aug	-0.1%		
Simple Error- Jan-Dec	0.8%		
MAPE Error- Jan-Aug	0.8%		
MAPE Error- Jan-Dec	1.8%		

The analysis shows that the October 2011 SCE billed month retail sales portrayed actual weather adjusted retail sales extremely well with the exception of the months of September and October. Up to August, the forecast Mean Absolute Error (MAPE) was just 0.8 percent. But for the year in total, the MAPE was 1.8 percent due largely to relatively high errors in September and October. September 2012 CDDs were 70 percent above normal and October CDDs were 120 percent above normal. The error in these two months is thus largely explained by temperatures in these 2 months that are outside the sample period upon which the weather normalization models were constructed.

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:

$$Y_t = x_t' ß + e_t$$

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:

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

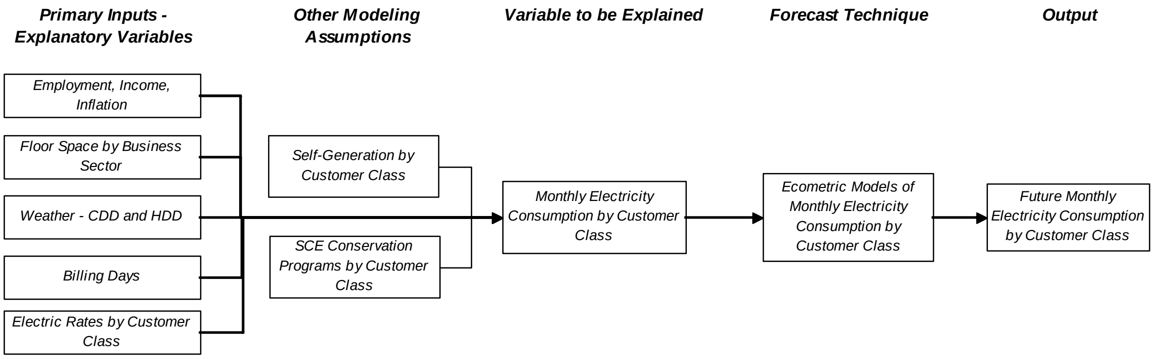
where s is the standard error of regression. These standard errors account for both innovation uncertainty (the first term) and coefficient uncertainty (the second term). Point forecasts made from linear regression models estimated by least squares are optimal in the sense that they have the smallest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

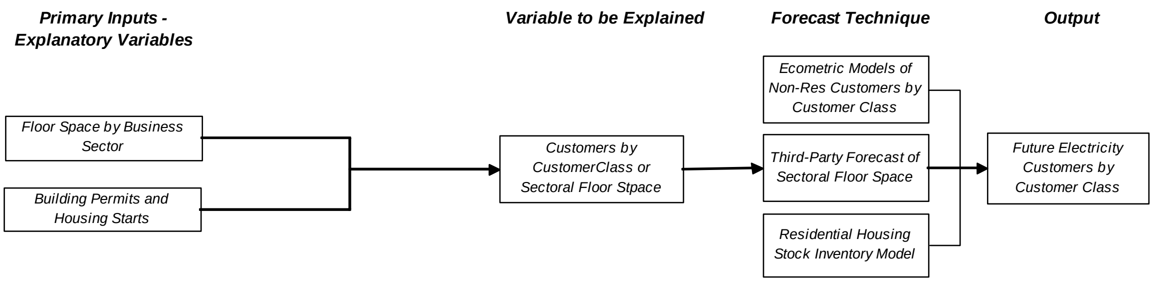
Exogenous variable uncertainty, i.e., uncertainty regarding future weather conditions, economic conditions, etc., is handled through the construction of forecast scenarios. For example, we typically include along with a base case forecast, alternative high and low economic case forecasts. Economic High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

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

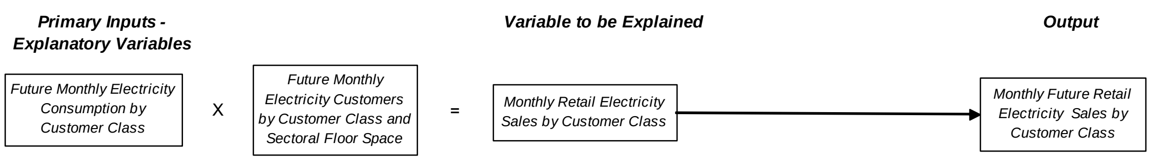
Electricity Consumption (kWh per Customer) Modeling and Forecasting



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+LAEE
Method: Least Squares
Sample: 2001M01 2012M07
Included observations: 139

Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
INTERCEPT	-125.4729	31.75869	-3.950821	0.0001
(LACDD)*SUMSEAS*LASIZE	0.000947	1.48E-05	63.99638	0.0000
(LAHDD)*WINSEAS*LASIZE	0.000183	7.95E-06	22.97241	0.0000
BDAYS	0.767196	0.025294	30.33079	0.0000
LAINCAVG	0.002338	0.000806	2.902697	0.0044
LARATE(-1)*CRISIS	-2.476769	1.363861	-1.815998	0.0720
LARATE(-1)*NOCRISIS	-2.674533	1.378403	-1.940313	0.0548
TR	1.220610	0.041201	29.62552	0.0000
JAN	43.69174	3.806956	11.47682	0.0000
APR	-16.17751	2.909927	-5.559420	0.0000
NOV	8.471135	3.236261	2.617568	0.0100
DEC	18.87239	3.509614	5.377342	0.0000
B0103	-31.41964	9.498243	-3.307943	0.0013
B1008	-34.49247	9.034579	-3.817828	0.0002
B0509	-34.35688	9.017807	-3.809893	0.0002
B0305	80.93620	9.315673	8.688176	0.0000
B0205	19.01731	4.686328	4.058042	0.0001
B0907	-42.88456	9.294033	-4.614204	0.0000
B1002	36.39961	9.118722	3.991744	0.0001
B1103	29.97059	9.448390	3.172032	0.0019
B0811	37.11501	9.061058	4.096101	0.0001
B0711	24.43091	9.020906	2.708254	0.0078
B0805	28.70583	9.269301	3.096871	0.0025

R-squared	0.991407	Mean dependent var	591.7144
Adjusted R-squared	0.989777	S.D. dependent var	87.52388
S.E. of regression	8.849476	Sum squared resid	9084.335
F-statistic	608.3118	Durbin-Watson stat	1.832692
Prob(F-statistic)	0.000000		

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

Residential Electricity Use Model – Orange County

Dependent Variable: ORUSE+ORPEE
Method: Least Squares
Sample: 2001M01 2012M07
Included observations: 139

Variable	***Coefficient***	**Std. Error**	***t-Statistic***	***Prob.***
INTERCEPT	-90.03259	37.85953	-2.378069	0.0190
(ORCDD/COOL)*SUMSEAS*ORSIZE	0.000747	1.75E-05	42.67335	0.0000
(ORHDD/HEAT)*WINSEAS*ORSIZE	0.000233	1.75E-05	13.29940	0.0000
BDAYS	0.891953	0.039368	22.65692	0.0000
ORRATE(-1)*CRISIS	-2.316937	1.504441	-1.540065	0.1262
ORRATE(-1)*NOCRISIS	-2.300672	1.513163	-1.520439	0.1311
ORINCAVG	0.000842	0.000507	1.661688	0.0993
TR	1.277142	0.035871	35.60364	0.0000
JAN	22.79423	5.693251	4.003728	0.0001
FEB	-23.51047	6.608205	-3.557770	0.0005
MAR	-24.98606	5.142360	-4.858871	0.0000
MAY	-21.31981	4.041723	-5.274932	0.0000
OCT	-13.57950	4.090262	-3.319958	0.0012
B0907	-60.59986	13.20275	-4.589943	0.0000
B0205	37.53201	13.22084	2.838852	0.0053
B0305	62.66775	13.25301	4.728569	0.0000
B0608	-57.86288	12.60590	-4.590141	0.0000
B1102	-35.70242	12.84706	-2.779035	0.0064
B0708	-37.12976	12.94302	-2.868709	0.0049
B0906	-36.47140	13.08088	-2.788145	0.0062
B0810	30.44543	12.59296	2.417655	0.0172
B0712	44.33623	12.66339	3.501134	0.0007

R-squared	0.981873	Mean dependent var	637.6791
Adjusted R-squared	0.978619	S.D. dependent var	84.76978
S.E. of regression	12.39516	Sum squared resid	17975.89
F-statistic	301.7816	Durbin-Watson stat	2.082515
Prob(F-statistic)	0.000000		

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

Residential Electricity Use Model – Riverside County

Dependent Variable: RIVUSE+RIVEE
Method: Least Squares
Sample: 2001M01 2012M07
Included observations: 139

Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
INTERCEPT	-198.0137	98.70648	-2.006086	0.0470
(RIVCDD/COOL)*SUMSEAS*RIVSIZE	0.000849	1.57E-05	54.24842	0.0000
(RIVHDD/HEAT)*WINSEAS*RIVSIZE	0.000146	1.75E-05	8.328431	0.0000
BDAYS	0.896869	0.069410	12.92125	0.0000
RIVRATE(-1)*CRISIS	-9.893565	3.354511	-2.949332	0.0038
RIVRATE(-1)*NOCRISIS	-9.022228	3.432339	-2.628595	0.0096
RIVINCAVG	0.010278	0.003480	2.953671	0.0038
JAN	37.63192	10.41124	3.614548	0.0004
MAY	-32.97259	9.439809	-3.492930	0.0007
AUG	53.57193	11.42761	4.687937	0.0000
NOV	39.92110	9.657308	4.133771	0.0001
TR	1.491127	0.073934	20.16841	0.0000
B1008	-112.4522	28.38308	-3.961945	0.0001
B0805	115.3360	30.00987	3.843270	0.0002
B0806	88.26292	30.21969	2.920709	0.0041
B0608	-81.84492	28.39880	-2.881985	0.0047
B0808	-82.98435	29.95485	-2.770314	0.0065
B1011	-72.22963	28.50646	-2.533799	0.0125

R-squared	0.985468	Mean dependent var	844.3888
Adjusted R-squared	0.983492	S.D. dependent var	216.9130
S.E. of regression	27.86976	Sum squared resid	97090.45
F-statistic	498.6398	Durbin-Watson stat	1.617047
Prob(F-statistic)	0.000000		

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

Residential Electricity Use Model – San Bernardino County

Dependent Variable: SBUSE+SBEE
Method: Least Squares
Sample: 2001M01 2012M07
Included observations: 139

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
INTERCEPT	-211.8404	58.73395	-3.606779	0.0005
(SBCDD/COOL)*SUMSEAS*SBSIZE	0.000873	9.88E-06	88.38483	0.0000
(SBHDD/HEAT)*WINSEAS*SBSIZE	0.000105	8.35E-06	12.55066	0.0000
BDAYS	0.808969	0.042080	19.22462	0.0000
SBRATE(-1)*CRISIS	-7.454166	2.284766	-3.262551	0.0015
SBRATE(-1)*NOCRISIS	-6.959710	2.340683	-2.973367	0.0036
SBINCAVG	0.008115	0.001948	4.166347	0.0001
TR	1.754618	0.045632	38.45190	0.0000
JAN	42.44463	6.547527	6.482543	0.0000
DEC	20.13111	6.186527	3.254024	0.0015
B0907	-76.99974	15.77956	-4.879715	0.0000
B0805	83.70719	15.82350	5.290054	0.0000
B0305	98.74667	15.93710	6.196026	0.0000
B1103	56.25074	15.56324	3.614333	0.0004
B1008	-67.26483	15.35708	-4.380052	0.0000
B0701	-51.74352	16.03433	-3.227046	0.0016
B0509	-57.45713	15.31317	-3.752138	0.0003
B1101	43.84972	16.03477	2.734664	0.0072
B0902	-47.46538	15.65815	-3.031353	0.0030
B0508	-39.40070	15.41291	-2.556345	0.0119
B0608	-48.30494	15.37557	-3.141669	0.0021
B0810	53.82004	15.44003	3.485748	0.0007
B0301	46.59339	16.45500	2.831564	0.0055
B0811	85.35006	15.54291	5.491254	0.0000

R-squared	0.992559	Mean dependent var	707.3000
Adjusted R-squared	0.990992	S.D. dependent var	159.2162
S.E. of regression	15.11097	Sum squared resid	26030.93
F-statistic	633.5981	Durbin-Watson stat	1.978883
Prob(F-statistic)	0.000000		

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

Residential Electricity Use Model – Ventura/Santa Barbara Counties

Dependent Variable: VENUSE+VENEE
Method: Least Squares
Sample: 2001M01 2012M07
Included observations: 139

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
INTERCEPT	37.93001	35.01386	1.083286	0.2809
(CDDY/COOL)*SUMSEAS*VENSIZE	9.34E-05	3.15E-06	29.61984	0.0000
(HDDY/HEAT)*WINSEAS*VENSIZE	0.000160	5.26E-06	30.41152	0.0000
BDAYS	0.752992	0.034001	22.14614	0.0000
VENRATE(-1)*CRISIS	-6.439190	1.493239	-4.312231	0.0000
VENRATE(-1)*NOCRISIS	-6.454733	1.475720	-4.373956	0.0000
VENINCAVG	0.001153	0.000467	2.467204	0.0150
TR	1.432625	0.035408	40.46064	0.0000
FEB	-38.86737	5.008257	-7.760658	0.0000
MAR	-21.52410	3.790756	-5.678049	0.0000
APR	-31.18592	3.528315	-8.838757	0.0000
B0101	33.78535	11.53624	2.928628	0.0041
B0305	54.53115	11.50233	4.740879	0.0000
B0806	63.44169	11.47030	5.530953	0.0000
B1002	43.18521	11.09527	3.892218	0.0002
B1104	-33.00809	11.16179	-2.957239	0.0037
B1204	-30.55445	11.28849	-2.706689	0.0078
B1007	28.65127	10.99602	2.605604	0.0103
B0706	36.46837	11.59404	3.145441	0.0021

R-squared	0.982968	Mean dependent var	645.9986
Adjusted R-squared	0.980413	S.D. dependent var	76.95221
S.E. of regression	10.76960	Sum squared resid	13918.12
F-statistic	384.7590	Durbin-Watson stat	2.001745
Prob(F-statistic)	0.000000		

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

Residential Electricity Use Model – Other (Rural) Counties

Dependent Variable: OTHUSE+OTHEE
Method: Least Squares
Sample: 2001M01 2012M07
Included observations: 139

Variable	***Coefficient***	***Std. Error***	*t-Statistic*	***Prob.***
INTERCEPT	-87.62656	55.78724	-1.570727	0.1191
(OTHCDD)*SUMSEAS*OTHSIZE	0.000835	9.52E-06	87.69061	0.0000
(OTHHDD/HEAT)*WINSEAS*OTHSIZE	0.000124	5.74E-06	21.66024	0.0000
BDAYS	0.792967	0.033164	23.91055	0.0000
RESRATE(-1)*CRISIS	-5.393196	1.710016	-3.153886	0.0021
RESRATE(-1)*NOCRISIS	-6.110317	1.714889	-3.563098	0.0005
OTHINCAVG	0.005184	0.001771	2.927750	0.0041
TR	1.511802	0.042693	35.41073	0.0000
JAN	42.56663	5.041938	8.442514	0.0000
APR	-17.38677	4.244210	-4.096586	0.0001
NOV	-16.79676	4.577087	-3.669750	0.0004
B0902	-53.74554	13.33055	-4.031757	0.0001
B0707	87.25097	13.39241	6.514955	0.0000
B0907	-82.72489	13.67753	-6.048234	0.0000
B0807	146.2228	13.45388	10.86844	0.0000
B0601	-74.71656	13.83985	-5.398655	0.0000
B0305	106.2277	13.36395	7.948830	0.0000
B0701	-53.74288	13.92389	-3.859761	0.0002
B0901	-85.25334	14.06217	-6.062601	0.0000
B0609	75.61171	13.25443	5.704637	0.0000
B0509	-72.53440	13.30511	-5.451619	0.0000
B0806	57.13335	13.59368	4.202935	0.0001
B0805	59.46586	13.67287	4.349186	0.0000
B0810	38.34494	13.32110	2.878512	0.0048
B2008	-29.52449	5.712425	-5.168469	0.0000
B0811	54.84762	13.35893	4.105688	0.0001

R-squared	0.995107	Mean dependent var	737.5345
Adjusted R-squared	0.993971	S.D. dependent var	166.5368
S.E. of regression	12.93081	Sum squared resid	18727.05
F-statistic	876.0819	Durbin-Watson stat	1.931445
Prob(F-statistic)	0.000000		

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

Commercial Electricity Use Model – Large Customers

Dependent Variable: COMUSEL+COMEEL
Method: Least Squares
Sample: 2000M06 2012M07
Included observations: 146

Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
INTERCEPT	-369.7999	55.20827	-6.698271	0.0000
(CDDY/COMCAC)*SUMSEAS	0.046474	0.005160	9.006058	0.0000
BDAYS	0.400241	0.024967	16.03101	0.0000
COMEMPLOY	31.35484	3.452262	9.082405	0.0000
COMRATEL(-1)*NOCRISIS	-2.252955	0.596602	-3.776314	0.0002
COMRATEL(-1)*CRISIS	-2.695426	0.621404	-4.337636	0.0000
TRL	0.671908	0.077495	8.670366	0.0000
BSHIFT	7.798653	1.649458	4.728010	0.0000
JAN	-18.92200	2.896247	-6.533280	0.0000
FEB	-6.456485	2.939315	-2.196595	0.0299
MAR	-14.69964	2.779047	-5.289455	0.0000
APR	-10.95424	2.531647	-4.326923	0.0000
AUG	15.51659	2.881604	5.384708	0.0000
DEC	-18.80178	2.855368	-6.584713	0.0000
B0801	52.29343	8.206927	6.371864	0.0000
B0105	-23.83167	7.972202	-2.989345	0.0034
B0907	-25.09212	7.954956	-3.154275	0.0020
B1004	24.36110	7.730600	3.151256	0.0020
B1100	-30.57746	8.209869	-3.724476	0.0003
B0702	20.10785	7.806003	2.575947	0.0112
B0711	19.59751	7.658802	2.558821	0.0117

R-squared	0.924387	Mean dependent var	300.0566
Adjusted R-squared	0.912289	S.D. dependent var	25.15752
S.E. of regression	7.450653	Sum squared resid	6939.029
F-statistic	76.40800	Durbin-Watson stat	2.461554
Prob(F-statistic)	0.000000		

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

Commercial Electricity Use Model – Small Customers

Dependent Variable: COMUSES+COMEES
Method: Least Squares
Sample: 2001M01 2012M07
Included observations: 146

Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
INTERCEPT	-2.845768	0.633234	-4.494026	0.0000
((CDDY*COMSIZE/COMCAC))*SUMSEAS	3.08E-07	1.91E-08	16.17290	0.0000
CUMBDAYS	0.005454	0.000224	24.29615	0.0000
COMEMPLOY	0.263983	0.039247	6.726240	0.0000
COMRATES(-1)*CRISIS	-0.058630	0.008052	-7.281663	0.0000
COMRATES(-1)*NOCRISIS	-0.055812	0.007789	-7.165569	0.0000
(DAYHRS*COMSIZE)/LIGHTINDX	5.42E-07	6.53E-08	8.286644	0.0000
TRS	0.007469	0.000940	7.949447	0.0000
APR	-0.098516	0.032095	-3.069542	0.0026
MAY	-0.107280	0.033664	-3.186820	0.0018
AUG	0.247002	0.037289	6.624014	0.0000
OCT	0.123535	0.032431	3.809163	0.0002
B0900	0.346280	0.106606	3.248241	0.0015
B0301	0.297918	0.103065	2.890579	0.0045
B0907	-0.285947	0.105149	-2.719438	0.0074
B1002	0.309235	0.105115	2.941872	0.0039

R-squared	0.961076	Mean dependent var	4.740274
Adjusted R-squared	0.956248	S.D. dependent var	0.468415
S.E. of regression	0.097978	Sum squared resid	1.238371
F-statistic	199.0698	Durbin-Watson stat	1.961065
Prob(F-statistic)	0.000000		

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

Industrial Electricity Use Model

Dependent Variable: INDUSE+INDEE
Method: Least Squares
Sample: 1995m01 2012M07
Included observations: 211

Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
INTERCEPT	-0.326910	0.247775	-1.319385	0.1886
(CDDX/CAC)*SUMSEAS	0.000688	0.000136	5.062278	0.0000
INDRATE*CRISIS	-0.022308	0.004538	-4.915475	0.0000
INDRATE*NOCRISIS	-0.014143	0.004568	-3.095962	0.0023
MANEMPLOY	0.966270	0.069976	13.80850	0.0000
BDAYS	0.002591	0.000241	10.74307	0.0000
TR	0.001073	0.000345	3.111789	0.0021
JAN	-0.116715	0.029420	-3.967253	0.0001
JUN	0.066191	0.026666	2.482205	0.0139
AUG	0.202777	0.032527	6.234077	0.0000
OCT	0.136334	0.027387	4.978119	0.0000
B0896	-0.396220	0.109027	-3.634146	0.0004
B0598	-0.410647	0.106127	-3.869390	0.0001
B0901	0.280586	0.110755	2.533384	0.0121
B1299	0.317624	0.113976	2.786768	0.0059
B1208	-0.295582	0.107985	-2.737245	0.0068
B0309	-0.262237	0.105963	-2.474792	0.0142
B2012	0.119152	0.039022	3.053444	0.0026

R-squared	0.879623	Mean dependent var	3.503801
Adjusted R-squared	0.869020	S.D. dependent var	0.288556
S.E. of regression	0.104432	Sum squared resid	2.104866
F-statistic	82.95858	Durbin-Watson stat	2.106718
Prob(F-statistic)	0.000000		

Other Public Authority Electricity Use Model

Dependent Variable: OPAUSE+OPAEE
Method: Least Squares
Sample (adjusted): 2000M06 2012M07
Included observations: 146

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
INTERCEPT	-0.082701	0.198604	-0.416413	0.6778
(CDDX/CAC)*SUMSEAS	0.003620	0.000264	13.72610	0.0000
OPARATE(-1)	-0.018334	0.006898	-2.657657	0.0089
GOVEMPLOY	0.233246	0.044112	5.287575	0.0000
BDAYS	0.001674	0.000172	9.710345	0.0000
BCLOSE	-0.131503	0.021289	-6.176942	0.0000
DAYHRS/LIGHTINDX	0.001100	0.000205	5.373319	0.0000
JUL	-0.161199	0.035294	-4.567357	0.0000
AUG	-0.146053	0.043337	-3.370161	0.0010
SEP	-0.161665	0.043451	-3.720610	0.0003
NOV	0.078038	0.023642	3.300806	0.0012
B0901	0.223291	0.078022	2.861916	0.0049
B0900	0.199823	0.079685	2.507658	0.0134
B0700	0.265069	0.078382	3.381767	0.0010
B0907	-0.253878	0.077617	-3.270889	0.0014
B0803	-0.216321	0.077287	-2.798946	0.0059
B0706	-0.342111	0.081273	-4.209388	0.0000

R-squared	0.921094	Mean dependent var	2.191151
Adjusted R-squared	0.911307	S.D. dependent var	0.242197
S.E. of regression	0.072130	Sum squared resid	0.671147
F-statistic	94.11568	Durbin-Watson stat	1.626639
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: 2000M01 2012M07
Included observations: 151

Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
INTERCEPT	-5.353945	0.810079	-6.609168	0.0000
BDAYS	0.007233	0.001050	6.888301	0.0000
AGEMPLOY	0.777655	0.062195	12.50343	0.0000
PRECIP(-1)	-0.215680	0.038880	-5.547266	0.0000
TR	0.011798	0.001147	10.28321	0.0000
JUN	1.433807	0.176419	8.127302	0.0000
JUL	2.725906	0.166892	16.33334	0.0000
AUG	3.171919	0.174789	18.14708	0.0000
SEP	2.316919	0.167824	13.80563	0.0000
OCT	1.142153	0.158864	7.189489	0.0000
B200708	0.543391	0.185285	2.932727	0.0040
B0409	1.324434	0.473482	2.797219	0.0059
B0312	1.536936	0.473467	3.246131	0.0015
B0302	1.056419	0.474193	2.227824	0.0276
B1208	-1.098464	0.478197	-2.297096	0.0232
B0612	2.009303	0.490305	4.098070	0.0001
PDL(RUNOFF)	-0.000116	2.33E-05	-4.966416	0.0000

The symbol (-1) indicates that the variable is lagged 1 period.
The PDL symbol indicates a Polynomial Distributed Lag variable

R-squared	0.953734	Mean dependent var	6.518351
Adjusted R-squared	0.948210	S.D. dependent var	2.035581
S.E. of regression	0.463245	Sum squared resid	28.75584
F-statistic	172.6451	Durbin-Watson stat	1.259257
Prob(F-statistic)	0.000000		

Lag Distribution of RUNOFF

	i	Coefficient	Std. Error	t-Statistic
`      *  .│`	0	-0.00011	2.1E-05	-4.96642
`    *    .│`	1	-0.00019	3.9E-05	-4.96642
`  *      .│`	2	-0.00026	5.2E-05	-4.96642
` *       .│`	3	-0.00031	6.2E-05	-4.96642
`*        .│`	4	-0.00034	6.8E-05	-4.96642
`*        .│`	5	-0.00035	7.0E-05	-4.96642
`*        .│`	6	-0.00034	6.8E-05	-4.96642
` *       .│`	7	-0.00031	6.2E-05	-4.96642
`  *      .│`	8	-0.00026	5.2E-05	-4.96642
`    *    .│`	9	-0.00019	3.9E-05	-4.96642
`      *  .│`	10	-0.00011	2.1E-05	-4.96642
Sum of Lags		-0.00276	0.00056	-4.96642

Street Light Electricity Use Model

Dependent Variable: STLTUSE
Method: Least Squares
Sample: 2001M06 2012M07
Included observations: 134

Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
INTERCEPT	0.735252	0.216998	3.388286	0.0010
CUMBDAYS	0.001008	6.90E-05	14.61462	0.0000
RESPRSTRLT	0.005011	0.000613	8.172261	0.0000
NIGHTHRS/LIGHTINDX	0.000962	5.10E-05	18.85892	0.0000
TR	-0.001637	0.000397	-4.121378	0.0001
B0610	0.293208	0.029632	9.894938	0.0000
B1106	-0.206698	0.029326	-7.048266	0.0000
B0608	-0.112582	0.029889	-3.766685	0.0003
B0105	-0.121504	0.030025	-4.046738	0.0001
B0506	0.110759	0.029296	3.780698	0.0002
B0405	-0.119747	0.029451	-4.065934	0.0001
B1006	-0.076231	0.029180	-2.612475	0.0101
B0204	-0.076988	0.029802	-2.583343	0.0110
B0107	0.077778	0.029650	2.623189	0.0098

R-squared	0.977304	Mean dependent var	3.141791
Adjusted R-squared	0.974846	S.D. dependent var	0.183179
S.E. of regression	0.029053	Sum squared resid	0.101286
F-statistic	397.4866	Durbin-Watson stat	1.918404
Prob(F-statistic)	0.000000		

8) Electricity Use Model Variable Description

Residential Electricity Use Model

ResUse	Recorded residential class monthly electricity consumption in kWh per customer. Source: SCE.
CDD	Cooling degree-days. 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.
ResEE	SCE residential class monthly energy efficiency program savings and by-pass avoided consumption in kWh per residential class customer. Source: SCE.
Inc	Constant $2005 dollar income per capita. Sources: Moody's Economy.Com.
BDays	Average number of days in monthly billing statement multiplied by the number of billing cycles in month. Source: SCE
Jan-Dec	Binary variable set equal to 1 for the designated month 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.
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.
Cool	An index measuring average efficiency of residential space cooling equipment. Source: Energy Information Administration.
Heat	An index measuring average efficiency of residential space heating equipment. Source: Energy Information Administration.
TR	Linear time trend variable counter designed to capture secular trend in electricity consumption not otherwise captured in the model.
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.
LA	Prefix in front of variable name to denote Los Angeles County.
OR	Prefix in front of variable name to denote Orange County.
SB	Prefix in front of variable name to denote San Bernardino County.

RIV	Prefix in front of variable name to denote Riverside County.
VEN	Prefix in front of variable name to denote Ventura and Santa Barbara Counties.
OTH	Prefix in front of variable name to denote Rural Counties (Fresno, Inyo, Kern Kings, Mono and Tulare)

Commercial Electricity Use Model

ComUse	Recorded commercial class monthly electricity consumption in MWh per commercial customer. Source: SCE.
CDD	Cooling degree-days, dynamic population share weighted. Source: SCE and National Weather Service
ComRate	Commercial class constant $2000 dollar price of electricity in cents per kWh. Source: SCE and Global Insight
ComEmploy	Service sector monthly employment per commercial class customer. Source: Global Insight.
ComEE	SCE commercial class monthly energy efficiency program savings and by-pass avoided consumption in MWh per commercial class 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 -Dec	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.
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.
CAC	An index measuring the average efficiency of central air conditioning equipment. Source: Energy Information Administration.
TR	Linear time trend variable counter designed to capture secular trend in electricity consumption not otherwise captured in the model.
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.
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	Recorded industrial class monthly electricity consumption 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.
ManEmploy	Manufacturing sector monthly employment per industrial building thousand square feet. Source: Global Insight and McGraw-Hill.
IndEE	SCE industrial class monthly energy efficiency program savings and by-pass avoided consumption in kWh per industrial building thousand 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
Jan-Dec	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.
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.
CAC	An index measuring the average efficiency of central air conditioning equipment. Source: Energy Information Administration.
TR	Linear counter variable designed to capture secular trend in industrial class electricity consumption not otherwise captured in the model.
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.

Other Public Authority Electricity Use Model

OPAUse	Recorded Other Public Authority class monthly electricity consumption in kWh per government building square feet. Source: SCE and McGraw-Hill.
CDD	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
OPAEmploy	Government employment per government building thousand square feet. Source: Global Insight and McGraw-Hill.
OPAEE	SCE Other Public Authority class monthly energy efficiency program savings and by-pass avoided consumption in kWh per government building thousand 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
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.
Jan-Dec	Binary variable set equal to 1 for the designated month and zero otherwise.
SumSeas	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.
TR	Linear time trend variable designed to capture secular trend in public authority class electricity consumption not otherwise captured in the model.
Hours	Binary variable equal to one for the period May 2009 onwards to Dec 2011 that portrays shortened office hours in state government buildings.
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 Electricity Use Model

AgUse	Recorded agriculture class monthly electricity consumption in MWh per agriculture customer. Source: SCE.
AgEE	SCE agriculture monthly energy efficiency program savings and by-pass consumption in MWh per agriculture class customer. Source: SCE
AgEmploy	Agriculture employment per agriculture class customer. Source: Global Insight and McGraw-Hill.
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.
PRECIP	Fresno monthly precipitation level in inches. Source: NOAA.
TR	Linear time trend variable designed to capture secular trend in public authority class electricity consumption not otherwise captured in the model.
Jan-Dec	Binary variable set equal to 1 for the designated month 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	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.
BDays	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.
TR	Linear time trend variable designed to capture secular trend in street lighting consumption not otherwise captured in the model.
Jan-Dec	Binary variable set equal to 1 for the designated month 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. The Residential customer models are constructed on the basis that new customers are determined mainly by housing starts (with a lag extending from 8 to 12 months depending upon the region). The housing start forecast is an average of forecasts from Moody's and IHS-GI.

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(LACUST)
Method: Least Squares
Sample: 2001M01 2012M07
Included observations: 139

Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
INTERCEPT	0.099092	0.083881	1.181346	0.2396
FEB	0.298596	0.117452	2.542289	0.0122
JUN	-0.372156	0.112432	-3.310049	0.0012
DEC	-0.242369	0.112466	-2.155051	0.0330
B0210	0.974532	0.376227	2.590273	0.0107
B0707	-0.958510	0.356720	-2.687009	0.0082
B0110	0.852838	0.359935	2.369419	0.0193
B0212	1.157727	0.357002	3.242914	0.0015
PDL(LASTART)	2.00E-05	3.73E-06	5.349599	0.0000

R-squared	0.375503	Mean dependent var	0.494532
Adjusted R-squared	0.337073	S.D. dependent var	0.435266
S.E. of regression	0.354395	Sum squared resid	16.32749
F-statistic	9.770957	Durbin-Watson stat	1.815832
Prob(F-statistic)	0.000000		

Lag Distribution of LASTART

```
                     i     Coefficient    Std. Error    t-Statistic

 .   *       |       0      1.8E-05        3.4E-06        5.34960
 .     *     |       1      3.2E-05        6.0E-06        5.34960
 .       *   |       2      4.2E-05        7.8E-06        5.34960
 .        *  |       3      4.8E-05        9.0E-06        5.34960
 .          *|       4      5.0E-05        9.3E-06        5.34960
 .        *  |       5      4.8E-05        9.0E-06        5.34960
 .       *   |       6      4.2E-05        7.8E-06        5.34960
 .     *     |       7      3.2E-05        6.0E-06        5.34960
 .   *       |       8      1.8E-05        3.4E-06        5.34960
```

Sum of Lags		0.00033	6.2E-05	5.34960

The D(.) symbol indicates the first difference.
The PDL symbol indicates a polynomial distributed lag.

Residential Electricity Customer Model – Orange County

Dependent Variable: D(ORCUST)
Method: Least Squares
Sample: 2001M02 2012M07
Included observations: 138

Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
INTERCEPT	0.197942	0.038586	5.129828	0.0000
JUN	-0.136096	0.055801	-2.438934	0.0161
B0303	-0.487979	0.179632	-2.716553	0.0075
B0112	-0.552226	0.178391	-3.095594	0.0024
B0212	0.649686	0.178408	3.641573	0.0004
PDL(ORSTART)	1.34E-05	2.02E-06	6.648683	0.0000

R-squared	0.366032	Mean dependent var	0.418116
Adjusted R-squared	0.342018	S.D. dependent var	0.218664
S.E. of regression	0.177372	Sum squared resid	4.152812
F-statistic	15.24250	Durbin-Watson stat	1.858247
Prob(F-statistic)	0.000000		

Lag Distribution of ORSTART

	i	Coefficient	Std. Error	t-Statistic
. * |	0	1.2E-05	1.9E-06	6.64868
. * |	1	2.3E-05	3.5E-06	6.64868
. * |	2	3.2E-05	4.8E-06	6.64868
. * |	3	3.8E-05	5.8E-06	6.64868
. * |	4	4.3E-05	6.5E-06	6.64868
. *|	5	4.6E-05	6.9E-06	6.64868
. *|	6	4.7E-05	7.1E-06	6.64868
. *|	7	4.6E-05	6.9E-06	6.64868
. * |	8	4.3E-05	6.5E-06	6.64868
. * |	9	3.8E-05	5.8E-06	6.64868
. * |	10	3.2E-05	4.8E-06	6.64868
. * |	11	2.3E-05	3.5E-06	6.64868
. * |	12	1.2E-05	1.9E-06	6.64868
Sum of Lags		0.00044	6.6E-05	6.64868

The D(.) symbol indicates the first difference.
The PDL symbol indicates a polynomial distributed lag.

Residential Electricity Customer Model – Riverside County

Dependent Variable: D(RIVCUST)
Method: Least Squares
Sample: 2001M02 2012M07
Included observations: 138

Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
INTERCEPT	0.101050	0.038619	2.616587	0.0099
JUL	0.230746	0.073043	3.159029	0.0020
B1008	-1.157120	0.243014	-4.761534	0.0000
B1108	0.695457	0.243048	2.861403	0.0049
B1207	-0.858273	0.242378	-3.541053	0.0006
B1202	0.648535	0.242549	2.673837	0.0085
B0306	0.721484	0.243778	2.959596	0.0037

R-squared	0.889123	Mean dependent var	1.071159
Adjusted R-squared	0.883153	S.D. dependent var	0.705770
S.E. of regression	0.241252	Sum squared resid	7.566354
F-statistic	148.9249	Durbin-Watson stat	1.364438
Prob(F-statistic)	0.000000		

Lag Distribution of RIVSTART

```
                    i     Coefficient    Std. Error    t-Statistic

 .  *       |       0      3.4E-05        1.1E-06       30.0952
 .     *    |       1      6.0E-05        2.0E-06       30.0952
 .       *  |       2      8.1E-05        2.7E-06       30.0952
 .         *|       3      9.4E-05        3.1E-06       30.0952
 .          *|      4      0.00010        3.3E-06       30.0952
 .          *|      5      0.00010        3.3E-06       30.0952
 .         *|       6      9.4E-05        3.1E-06       30.0952
 .       *  |       7      8.1E-05        2.7E-06       30.0952
 .     *    |       8      6.0E-05        2.0E-06       30.0952
 .  *       |       9      3.4E-05        1.1E-06       30.0952

Sum of Lags                0.00074        2.5E-05       30.0952
```

The D(.) symbol indicates the first difference.
The PDL symbol indicates a polynomial distributed lag.

Residential Electricity Customer Model – San Bernardino County

Dependent Variable: D(SBCUST)
Method: Least Squares
Sample: 2001M02 2012M07
Included observations: 138

Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
INTERCEPT	0.180084	0.031583	5.701922	0.0000
NOV	-0.179577	0.063359	-2.834273	0.0053
DEC	-0.198144	0.063332	-3.128642	0.0022
B0908	-0.735695	0.199160	-3.694000	0.0003
B1007	-0.710690	0.118023	-6.021643	0.0000
B0308	-0.595831	0.101144	-5.890921	0.0000
B0604	-0.466505	0.199510	-2.338260	0.0209
PDL01	3.27E-05	1.55E-06	21.12108	0.0000

R-squared	0.818112	Mean dependent var	0.646232
Adjusted R-squared	0.808318	S.D. dependent var	0.451764
S.E. of regression	0.197789	Sum squared resid	5.085667
F-statistic	83.53226	Durbin-Watson stat	1.820891
Prob(F-statistic)	0.000000		

Lag Distribution of SBSTART

```
                     i    Coefficient   Std. Error   t-Statistic

 .   *       |       0     3.0E-05       1.4E-06      21.1211
 .      *    |       1     5.3E-05       2.5E-06      21.1211
 .        *  |       2     7.1E-05       3.4E-06      21.1211
 .         * |       3     8.3E-05       3.9E-06      21.1211
 .          *|       4     8.9E-05       4.2E-06      21.1211
 .          *|       5     8.9E-05       4.2E-06      21.1211
 .         * |       6     8.3E-05       3.9E-06      21.1211
 .        *  |       7     7.1E-05       3.4E-06      21.1211
 .      *    |       8     5.3E-05       2.5E-06      21.1211
 .   *       |       9     3.0E-05       1.4E-06      21.1211

Sum of Lags                0.00065       3.1E-05      21.1211
```

The D(.) symbol indicates the first difference.
The PDL symbol indicates a polynomial distributed lag.

Residential Electricity Customer Model – Ventura/Santa Barbara Counties

Dependent Variable: D(VENCUST)
Method: Least Squares
Sample: 2002M06 2012M07
Included observations: 122

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
C	0.028586	0.016074	1.778389	0.0781
JUN	-0.403867	0.029329	-13.77019	0.0000
JUL	0.112420	0.028119	3.998069	0.0001
SEP	0.228224	0.030733	7.426130	0.0000
OCT	0.089711	0.029328	3.058879	0.0028
B0906	0.291298	0.092172	3.160380	0.0020
B1208	-0.281661	0.088051	-3.198855	0.0018
B0806	0.320182	0.088070	3.635545	0.0004
B0208	-0.247312	0.087924	-2.812793	0.0058
PDL01	1.91E-05	1.78E-06	10.70123	0.0000

R-squared	0.817235	Mean dependent var	0.168852
Adjusted R-squared	0.802549	S.D. dependent var	0.196461
S.E. of regression	0.087299	Sum squared resid	0.853555
F-statistic	55.64550	Durbin-Watson stat	2.111486
Prob(F-statistic)	0.000000		

Lag Distribution of VENSTART

```
                      i      Coefficient    Std. Error    t-Statistic

 .  *        |        0      1.8E-05        1.7E-06       10.7012
 .     *     |        1      3.3E-05        3.1E-06       10.7012
 .       *   |        2      4.5E-05        4.2E-06       10.7012
 .         * |        3      5.5E-05        5.1E-06       10.7012
 .          *|        4      6.1E-05        5.7E-06       10.7012
 .           *|       5      6.5E-05        6.1E-06       10.7012
 .           *|       6      6.7E-05        6.2E-06       10.7012
 .           *|       7      6.5E-05        6.1E-06       10.7012
 .          *|        8      6.1E-05        5.7E-06       10.7012
 .         * |        9      5.5E-05        5.1E-06       10.7012
 .       *   |        10     4.5E-05        4.2E-06       10.7012
 .     *     |        11     3.3E-05        3.1E-06       10.7012
 .  *        |        12     1.8E-05        1.7E-06       10.7012

Sum of Lags                  0.00062        5.8E-05       10.7012
```

The D(.) symbol indicates the first difference.
The PDL symbol indicates a polynomial distributed lag.

Residential Electricity Customer Model – OTHER (RURAL) Counties

Dependent Variable: D(OTHCUST)
Method: Least Squares
Sample: 2002M02 2012M07
Included observations: 126

Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
INTERCEPT	-0.021669	0.020303	-1.067240	0.2880
B1208	-0.262010	0.100473	-2.607770	0.0103
B0207	0.255831	0.100943	2.534414	0.0125
PDL(OTHSTART)	1.45E-05	9.82E-07	14.76067	0.0000

R-squared	0.670146	Mean dependent var	0.247778
Adjusted R-squared	0.662035	S.D. dependent var	0.171851
S.E. of regression	0.099905	Sum squared resid	1.217680
F-statistic	82.62035	Durbin-Watson stat	2.284277
Prob(F-statistic)	0.000000		

Lag Distribution of OTHSTART

```
                      i     Coefficient   Std. Error   t-Statistic

 .  *        |        0     1.3E-05       9.1E-07      14.7607
 .     *     |        1     2.5E-05       1.7E-06      14.7607
 .       *   |        2     3.4E-05       2.3E-06      14.7607
 .        *  |        3     4.1E-05       2.8E-06      14.7607
 .          *|        4     4.7E-05       3.2E-06      14.7607
 .           *|       5     5.0E-05       3.4E-06      14.7607
 .           *|       6     5.1E-05       3.4E-06      14.7607
 .           *|       7     5.0E-05       3.4E-06      14.7607
 .          *|        8     4.7E-05       3.2E-06      14.7607
 .        *  |        9     4.1E-05       2.8E-06      14.7607
 .       *   |        10    3.4E-05       2.3E-06      14.7607
 .     *     |        11    2.5E-05       1.7E-06      14.7607
 .  *        |        12    1.3E-05       9.1E-07      14.7607

Sum of Lags                 0.00047       3.2E-05      14.7607
```

The D(.) symbol indicates the first difference.
The PDL symbol indicates a polynomial distributed lag.

Commercial Customer Model – Small Customers

Dependent Variable: D(COMCUSTS)
Method: Least Squares
Sample (adjusted) 2001M06 2012M07
Included observations: 134 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
INTERCEPT	-74.60303	43.92357	-1.698474	0.0919
B0601	-695.0356	219.6244	-3.164656	0.0020
B0701	1149.403	221.2386	5.195312	0.0000
B1002	830.2081	218.9178	3.792328	0.0002
B0209	1099.018	224.7144	4.890732	0.0000
B0609	1011.285	220.2090	4.592389	0.0000
B0902	-549.3728	226.8297	-2.421962	0.0169
D(COMCUSTS(-1))	0.559037	0.066175	8.447796	0.0000
PDL(RESCUST)	0.006401	0.001057	6.057558	0.0000

R-squared	0.825440	Mean dependent var	795.1418
Adjusted R-squared	0.814268	S.D. dependent var	504.8146
S.E. of regression	217.5579	Sum squared resid	5916429.
F-statistic	73.88589	Durbin-Watson stat	2.000776
Prob(F-statistic)	0.000000		

Lag Distribution of D(RESCUST)

```
                     i    Coefficient   Std. Error   t-Statistic

 .   *        |      0    0.00582       0.00096      6.05756
 .       *    |      1    0.01047       0.00173      6.05756
 .         *  |      2    0.01397       0.00231      6.05756
 .           *|      3    0.01629       0.00269      6.05756
 .            *|     4    0.01746       0.00288      6.05756
 .            *|     5    0.01746       0.00288      6.05756
 .           *|      6    0.01629       0.00269      6.05756
 .         *  |      7    0.01397       0.00231      6.05756
 .       *    |      8    0.01047       0.00173      6.05756
 .   *        |      9    0.00582       0.00096      6.05756

Sum of Lags               0.12803       0.02114      6.05756
```

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.

Commercial Customer Model – Large Customers

Dependent Variable: COMCUSTL)
Method: Least Squares
Sample (adjusted) 2002M01 2012M07
Included observations: 128 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
INTERCEPT	-2603.889	52.69726	-49.41222	0.0000
B2009	142.4965	7.463442	19.09260	0.0000
B2012	-105.6873	14.17182	-7.457567	0.0000
PDL(Comflstck)	0.029031	0.000224	129.8099	0.0000

R-squared	0.994520	Mean dependent var	4323.732
Adjusted R-squared	0.994387	S.D. dependent var	390.5398
S.E. of regression	29.25977	Sum squared resid	105304.5
F-statistic	7441.352	Durbin-Watson stat	0.568180
Prob(F-statistic)	0.000000		

Lag Distribution of COMFLSTCK

```
                      i     Coefficient    Std. Error    t-Statistic

 . *         |        0     0.02791        0.00022       129.810
 .   *       |        1     0.05360        0.00041       129.810
 .     *     |        2     0.07704        0.00059       129.810
 .      *    |        3     0.09826        0.00076       129.810
 .        *  |        4     0.11724        0.00090       129.810
 .         * |        5     0.13399        0.00103       129.810
 .          *|        6     0.14851        0.00114       129.810
 .          *|        7     0.16079        0.00124       129.810
 .          *|        8     0.17084        0.00132       129.810
 .          *|        9     0.17865        0.00138       129.810
 .           *|       10    0.18424        0.00142       129.810
 .           *|       11    0.18759        0.00145       129.810
 .           *|       12    0.18870        0.00145       129.810
 .           *|       13    0.18759        0.00145       129.810
 .           *|       14    0.18424        0.00142       129.810
 .          *|        15    0.17865        0.00138       129.810
 .          *|        16    0.17084        0.00132       129.810
 .          *|        17    0.16079        0.00124       129.810
 .          *|        18    0.14851        0.00114       129.810
 .         * |        19    0.13399        0.00103       129.810
 .        *  |        20    0.11724        0.00090       129.810
 .      *    |        21    0.09826        0.00076       129.810
 .     *     |        22    0.07704        0.00059       129.810
 .   *       |        23    0.05360        0.00041       129.810
 . *         |        24    0.02791        0.00022       129.810

Sum of Lags                 3.26600        0.02516       129.810
```

The PDL symbol indicates a polynomial distributed lag.

Industrial Customer Model

Dependent Variable: D(INDCUST)
Method: Least Squares
Sample (adjusted): 1994M01 2012M07
Included observations: 223

Variable	Coefficient	Std. Error	t-Statistic	Prob.
INTERCEPT	-75.49598	17.84943	-4.229601	0.0000
TR	0.144644	0.108659	1.331172	0.1846
B0499	-491.0759	96.96875	-5.064270	0.0000
B0799	-623.0285	96.95745	-6.425793	0.0000
B0201	-436.9693	96.95981	-4.506705	0.0000
B0199	348.6578	97.55273	3.574044	0.0004
B0299	316.9026	97.11576	3.263143	0.0013
B0599	-382.9033	96.96829	-3.948748	0.0001
B0699	-317.7722	97.01196	-3.275598	0.0012
B0899	-526.7727	96.95452	-5.433194	0.0000
B0999	-359.3637	96.96603	-3.706079	0.0003
PDL(MANEMPLOY)	1.680525	0.266043	6.316742	0.0000

R-squared	0.501277	Mean dependent var	-84.85202
Adjusted R-squared	0.475278	S.D. dependent var	133.3700
S.E. of regression	96.61023	Sum squared resid	1969376.
F-statistic	19.28007	Durbin-Watson stat	0.754472
Prob(F-statistic)	0.000000		

.

Lag Distribution of D(MANEMPLOY)

```
                    i     Coefficient   Std. Error   t-Statistic

 .          *|      0     2.80088       0.44340      6.31674
 .         * |      1     2.52079       0.39906      6.31674
 .        *  |      2     2.24070       0.35472      6.31674
 .      *    |      3     1.96061       0.31038      6.31674
 .     *     |      4     1.68053       0.26604      6.31674
 .    *      |      5     1.40044       0.22170      6.31674
 .   *       |      6     1.12035       0.17736      6.31674
 .  *        |      7     0.84026       0.13302      6.31674
 . *         |      8     0.56018       0.08868      6.31674
 .*          |      9     0.28009       0.04434      6.31674

Sum of Lags                15.4048       2.43873      6.31674.
```

The D(.) symbol indicates the first difference.
The PDL symbol indicates a polynomial distributed lag.

Other Public Authority Customer Model

Dependent Variable: D(OPACUST)
Method: Least Squares
Sample: 2001M03 2012M07
Included observations: 137

Variable	Coefficient	Std. Error	t-Statistic	Prob.
INTERCEPT	-42.43516	4.414837	-9.611942	0.0000
MAY	12.71571	3.794875	3.350759	0.0011
JUL	-8.876174	3.621970	-2.450648	0.0157
B0502	-32.86585	12.06810	-2.723366	0.0074
B0304	35.17143	11.48880	3.061368	0.0027
B0104	-54.35952	11.47659	-4.736555	0.0000
B0508	-46.88587	11.98452	-3.912204	0.0002
B0601	-84.61381	11.55825	-7.320644	0.0000
B0701	72.71826	12.74119	5.707337	0.0000
B0205	-82.26598	11.64272	-7.065872	0.0000
B1109	41.03885	11.51714	3.563286	0.0005
B1207	-49.26562	11.52233	-4.275665	0.0000
B0107	-29.76395	11.55153	-2.576623	0.0112
B0602	-26.95549	11.56430	-2.330922	0.0214
D(OPACUST(-1))	0.073679	0.051304	1.436137	0.1536
PDL(OPAFLSTCK)	0.002621	0.000816	3.213230	0.0017

R-squared	0.678094	Mean dependent var	-34.73723
Adjusted R-squared	0.635173	S.D. dependent var	18.90894
S.E. of regression	11.42117	Sum squared resid	15653.17
F-statistic	15.79873	Durbin-Watson stat	1.686784
Prob(F-statistic)	0.000000		

Lag Distribution of D(OPAFLSTCK)

```
                  i     Coefficient   Std. Error   t-Statistic

 .   *     |      0      0.00229      0.00071      3.21323
 .      *  |      1      0.00393      0.00122      3.21323
 .        *|      2      0.00492      0.00153      3.21323
 .         *|     3      0.00524      0.00163      3.21323
 .        *|      4      0.00492      0.00153      3.21323
 .      *  |      5      0.00393      0.00122      3.21323
 .   *     |      6      0.00229      0.00071      3.21323

Sum of Lags              0.02753      0.00857      3.21323
```

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.

Agriculture Customer Model

Dependent Variable: D(AGCUST)
Method: Least Squares
Sample: 1993M06 2012M07
Included observations: 230

Variable	Coefficient	Std. Error	t-Statistic	Prob.
INTERCEPT	-16.88663	4.692057	-3.598982	0.0004
D(AGCUST(-1))	0.517829	0.050396	10.27517	0.0000
D(AGEMPLOY)	0.512093	0.134763	3.799943	0.0002
TR	0.060086	0.026680	2.252084	0.0253
B0599	481.3658	26.07284	18.46235	0.0000
B0699	-810.7137	37.55037	-21.59003	0.0000
B0799	262.8646	36.13497	7.274521	0.0000
B0195	-76.04366	25.38600	-2.995496	0.0031
B0497	93.02762	25.58965	3.635361	0.0003
B0605	69.11524	25.25174	2.737049	0.0067
B0305	-67.92927	25.31925	-2.682910	0.0079
B1204	-74.00180	25.24975	-2.930794	0.0037
B1099	73.11105	25.33208	2.886105	0.0043
B0911	-62.58133	25.35772	-2.467940	0.0144
B0707	63.09195	25.29477	2.494269	0.0134

R-squared	0.838874	Mean dependent var	-15.88696
Adjusted R-squared	0.828382	S.D. dependent var	60.77775
S.E. of regression	25.17830	Sum squared resid	136298.6
F-statistic	79.95402	Durbin-Watson stat	2.105882
Prob(F-statistic)	0.000000		

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

Street Light Customer Model

Dependent Variable: D(STLTCUST)
Method: Least Squares
Sample: 2001M01 2012M07
Included observations: 139

Variable	Coefficient	Std. Error	t-Statistic	Prob.
INTERCEPT	18.85429	5.541985	3.402081	0.0009
D(STRCUST(-1))	0.077367	0.042940	1.801756	0.0740
AUG	-42.06275	8.391351	-5.012632	0.0000
B0209	84.01906	26.32540	3.191558	0.0018
B0101	-208.5819	25.56188	-8.159879	0.0000
B1006	-108.6483	25.75770	-4.218089	0.0000
B0202	-108.6439	25.58728	-4.246012	0.0000
B0602	-115.3073	25.56264	-4.510777	0.0000
B1106	93.92751	26.13692	3.593671	0.0005
B1108	-250.4493	25.86741	-9.682040	0.0000
B0109	99.60217	25.85559	3.852249	0.0002
B0504	-74.51106	25.65775	-2.904037	0.0044
B0809	-285.9370	26.97157	-10.60142	0.0000
B1109	-124.6643	25.76774	-4.837999	0.0000
B0512	-65.39360	25.73521	-2.541017	0.0123
PDL(RESCUST)	0.180774	0.050536	3.577122	0.0005

R-squared	0.804430	Mean dependent var	28.77698
Adjusted R-squared	0.780579	S.D. dependent var	54.30257
S.E. of regression	25.43660	Sum squared resid	79583.52
F-statistic	33.72862	Durbin-Watson stat	1.569193
Prob(F-statistic)	0.000000		

Lag Distribution of D(RESCUST)

```
                     i      Coefficient    Std. Error    t-Statistic

. *         |        0       0.16786        0.04693       3.57712
.    *      |        1       0.30990        0.08663       3.57712
.      *    |        2       0.42611        0.11912       3.57712
.        *  |        3       0.51650        0.14439       3.57712
.         * |        4       0.58106        0.16244       3.57712
.          *|        5       0.61980        0.17327       3.57712
.          *|        6       0.63271        0.17688       3.57712
.          *|        7       0.61980        0.17327       3.57712
.         * |        8       0.58106        0.16244       3.57712
.        *  |        9       0.51650        0.14439       3.57712
.      *    |       10       0.42611        0.11912       3.57712
.    *      |       11       0.30990        0.08663       3.57712
. *         |       12       0.16786        0.04693       3.57712

Sum of Lags                  5.87517        1.64243       3.57712
```

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

10) Customer Model Variable Description

Residential Customer Models

ResCust	Recorded number of residential class customers. Source: SCE.
PDL(HSTART)	Polynomial distributed lag of residential housing starts. Source: Moody's and IHS-GI.
LA	Prefix in front of variable name to denote Los Angeles County.
OR	Prefix in front of variable name to denote Orange County.
SB	Prefix in front of variable name to denote San Bernardino County.
RIV	Prefix in front of variable name to denote Riverside County.
VEN	Prefix in front of variable name to denote Ventura and Santa Barbara Counties.
OTH	Prefix in front of variable name to denote Rural Counties (Fresno, Inyo, Kern Kings, Mono and Tulare)
Jan-Dec	Binary variable set equal to 1 for the designated month 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 customer data.

Commercial Customer Models

ComCust	Recorded number of commercial class customers. Source: SCE.
PDL(RESCUST)	Polynomial distributed lag of residential customers. Source: SCE
PDL(COMFLSTCK)	Polynomial distributed lag of Commercial building total square footage. Source: McGraw-Hill..
Bmmyy	Binary variables equal to one on a particular month and year, 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.

PDL(MANEMPLOY)
Polynomial distributed lag of manufacturing employment. Source: Global Insight.

Bmmyy Binary variable equal to one on a particular month and year, 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.

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

PDL(OPAFLSTCK)
Polynomial distributed lag of government building floor stock. Source: McGraw-Hill.

Bmmyy Binary variables equal to one on a particular month and year, and zero otherwise, that are designed to capture billing irregularities in customer data.

Agriculture Customer Model

AgCust	Recorded 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 customer data.

Street Light Customer Model

StLtCust	Recorded number of street lighting customers. Source: SCE.
PDL(RERSCUST)	Polynomial distributed lag of number of residential customers. Source: SCE.
Jan-Dec	Binary variable set equal to 1 for the designated month 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 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 Electricty Sales - Economic and Demographic Drivers

Average Annual Rates of Change

	Customers	Electric Rate	Energy Efficiency	Thermal & Solar ByPass	Real Income per Capita *	Household Size
2001-2011	0.9%	1.8%	16.4%	53.7%	1.0%	0.6%
2011-2016	0.7%	5.9%	3.0%	27.3%	2.6%	0.2%
2016-2024	0.9%	2.1%	2.8%	6.2%	0.8%	0.2%
2011-2024	0.9%	3.5%	2.8%	13.9%	1.5%	0.2%

* Refers to L.A. County.

Commercial Electricty Sales - Economic and Demographic Drivers

Average Annual Rates of Change

	Customers	Electric Rate	Energy Efficiency	Thermal & Solar ByPass	Commercial Employment	Commercial Floor Stock
2001-2011	2.0%	1.0%	8.5%	19.2%	0.5%	1.6%
2011-2016	1.2%	6.7%	3.5%	8.3%	2.0%	0.8%
2016-2024	1.8%	2.1%	2.0%	5.0%	0.9%	1.2%
2011-2024	1.5%	3.8%	2.6%	6.3%	1.3%	1.0%

Industrial Electricty Sales - Economic and Demographic Drivers

Average Annual Rates of Change

	Customers	Electric Rate	Energy Efficiency	Thermal & Solar ByPass	Manufacturing Employment	Manufacturing Floor Stock
2001-2011	-6.3%	-0.3%	1.2%	2.7%	-3.3%	-0.3%
2011-2016	-3.0%	6.7%	3.5%	4.5%	0.8%	-0.2%
2016-2024	-3.8%	2.1%	1.0%	1.6%	-0.6%	0.0%
2011-2024	-3.5%	3.8%	2.0%	2.7%	0.0%	-0.1%

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.