SDG&E' Short-Term Demand Response Forecasting System

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ABSTRACT

As part of the Market Redesign and Technology Upgrade (MRTU), the California Independent System Operator (CAISO) created a set of goals to increase California's electric capacity by managing system demand through demand-response programs. A key element of making demand response a viable operational resource is an accurate forecast of the available hourly, curtailable demand that can be dispatched at the direction of the CASIO when resource or economic conditions require load reduction. SDG&E is committed to the goal of providing the CAISO with a forecast of the dispatchable demand response that can be expected from the bundle of demand response programs offered by the company. This paper discusses the Demand Response Forecasting System that SDG&E deployed to meet this goal and the performance of the system during the fall of 2008.

Introduction

As part of the September 21, 2006 Market Redesign and Technology Upgrade (MRTU) FERC Order[1], the California Independent System Operator (CAISO) created a set of goals to increase California's electric capacity by managing system demand through demand-response programs. A key element of making demand response a viable operational resource is an accurate forecast of the available hourly, curtailable demand that can be dispatched at the direction of the CASIO when resource or economic conditions require load reduction.

SDG&E is committed to the goal of providing the CAISO with a forecast of the dispatchable demand response that can be expected from the bundle of demand response programs offered by the company. To meet this goal, SDG&E worked with Itron to create a state-of-the-art short-term load forecast system for the purpose of generating day-of and day-ahead load reduction forecasts by demand response program. When SDGE initiates a demand response event, the resulting load reduction forecasts are then submitted by SDG&E to the CAISO as a bundled dispatchable demand response.

The paper begins with a description of the Demand Response Programs offered by SDG&E. This is followed by a description of the forecast model specifications. The forecasts derived by the forecast models are then compared to actual load shedding activity for two load response events called in October 2008. We conclude with an assessment of the forecast approach employed and the possible extensions of the framework as SDG&E rolls out smart metering to all of its customers.

SDG&E Demand Response Programs

SDGE currently offers 11 demand response programs[2] to its customers and has active participation in

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[1] [1] *Order Conditionally Accepting The California Independent System Operator's Electric Tariff Filing To Reflect Market Redesign And Technology Upgrade*, 116 FERC 61,274 (September 21, 2006), Pages 195-200, Docket Nos. ER06-615-000, et al.,

[2] Demand Response Program Details Can be Viewed on SDGE's Tariff website at www.sdge.com/regulatory/currenteffectivetariffs.shtml

nine of these programs. The demand response programs can be grouped into three basic categories. Price-driven programs rely on customers to make sound economic decisions to reduce load during high price hours. Voluntary or contractually obligated programs rely on customers to shut down equipment when they are notified that the system is nearing capacity. Direct load control programs use central dispatching of load control signals that automatically turn off or cycle customer end-use equipment. Within these categories, demand response programs are further classified as day-of or day-ahead load reduction. The specific demand response programs offered by SDG&E are summarized below.

Demand Response Programs	**Description**	**Emergency-Responsive**	**Price-Responsive**	**Direct Load Control**	**Day-of**	**Day-Ahead**
Critical Peak Pricing-E	TOU rate with increased cost during 'critical' periods and reduced commodity rate rest of year	X	-	-	X	-
Optional Binding Mandatory Curtailment	Customers can exempt a specific circuit(s) from rotating outages by reducing load when requested	X	-	-	X	-
Peak Generation	Customers earn incentives by transferring load from SDGE system to a standby generator	X		-	X	-
Base Interruptible Program	Customers receive monthly capacity payments in turn for load reduction when requested	-	X	-	X	-
CleanGen Program	A third party generator load reduction program: SDGE remotely dispatches customer generators.	X		-	X	-
Scheduled Load Reduction Program	Customers can schedule load reduction, in advance, for weekday hours during summer months	-	X	-	X	-
Demand Bidding Program	A voluntary, day-ahead or day-of "bid-in" load reduction program	-	X	-	X	X
Capacity Bidding Program	Customers receive monthly capacity payments (and energy incentives) in return for load reduction	-	X	-	X	X
Critical Peak Pricing Default	TOU rate with increased cost during 'critical' periods and reduced commodity rate rest of year	-	X	-	-	X
Commercial & Industrial Peak Day Credit	Reduce 10-20% on 'critical' days and receive 10-20% discount on all (on peak) charges for the month	-	X	-	-	X
Summer Saver	Residential & Small Business customers receive an incentive for central A/C cycling during peak periods	-	-	X	X	-

Demand Response Forecast Model Specifications

This section describes the demand response forecasting models and the forecast framework. The demand response forecast framework that SDG&E utilizes is based on a set of day-ahead load forecasting models. The regression-based forecasting models take into account load variation due to calendar conditions (e.g., day-of-the-week, holidays, season), weather conditions, and previous demand response events.

Once the load forecast models are estimated, they are used in a two-step process to estimate hourly load reduction. First, given weather forecasts and an assumption that no demand events will take place, the models are used to forecast hourly loads for the balance of the day through the end of the following day. This gives a forecast of loads that can be expected if customers do not under take demand response activity. Second, the models are used to forecast hourly loads with a demand event in place. This gives a forecast of loads that can be expected with demand response activity in place. The difference between the two load shapes provides a forecast of the load shedding potential.

Forecast Model Specification

To develop the demand response forecasting models, the interval-metered data for the customers that participated in 2007 demand response programs were analyzed to understand historical demand response activity. This analysis uncovered three modeling challenges the solutions to these challenges guided the model specifications used to develop forecasts of load shedding activity.

Scaling. First, the number of active participants in each demand response program can change on a daily basis. This means that as program participation grows models that are estimated using interval data for active program participants in 2007 could grossly under predict load shedding activity in 2008. Fortunately, SDG&E collects data on the size on each program participant. For all commercial TOU participants, SDG&E collects data on Peak kW. For the AC Saver participants, SDG&E collects data on the size (i.e. ton) of the air conditioning units that are on cycle controls. This allows the 2007 interval meter data to be normalized on a per-kW or per-ton basis. Forecasts from the resulting models are then in units of Load Shed Per kW or Load Shed per Ton. These values are then multiplied by the total active kW or Tons to produce load forecasts with and without load control events. Expressed as a formula, the dependent variable for the AC Saver forecast models is computed as follows:

$$LoadPerTon_{y,m,d}^{h} = \frac{\sum_{c \in Active} Load_{y,m,d,c}^{h}}{\sum_{c \in Active} ACTon_{y,m,d,c}}$$

Here, the Load Per Ton for all active customers in year (y), month (m), day (d) and hour (h) is computed as the ratio of total interval metered data for all active customers over the corresponding AC tonnage. For other programs the 2006 interval data are scaled on a peak kW basis. Load forecasts are then computed as the product of the predicted load per ton and the total tonnage of active program participants. Specifically,

$$LoadForecast_{y,md,d}^{h} = LoadPerTonForecast_{y,m,d}^{h} \times \sum_{c \in Active} ACTon_{y,m,d,c}$$

Model Structure. The second modeling challenge is that individual customer loads or in this case a small sample of individual customer loads tends to be very volatile. Unlike system loads that are relatively smooth because they are the composite of the load behavior of millions of customers, the loads for a single customer (especially residential customers) can vary due to unique behavior. This means the model specifications need to at once be sufficiently rich to capture the load shed impact of a demand response event while sufficiently parsimonious to cut through erratic loads. To address this challenge regression-based models are developed. For each demand response program a separate set of 24 hourly load forecasting equations are estimated. The estimated equations contain the following explanatory variables:

- **Day-of-the-Week Binary Variables –** these variables capture systematic load variation due to the day of the week.
- **Holiday Binary Variables –**Holiday binary variables are used to capture the load change due to observance of these holidays
- **Monthly Binary Variables –**Monthly binary variables are introduced to account for systematic load variation during these months
- **Heating & Cooling Degree Day Variables** - HDD and CDD variables are introduced to capture the influence of temperatures on loads. These variables are also interacted with a weekend binary to allow the weather response to be different between week days and weekend days. A weighted average of the prior two days of HDD and CDD data are introduced to capture the build up effect of temperature on heating and cooling loads. The HDD and CDD variables are constructed from hourly temperature and humidity data. A summer simmer index is constructed to bind these two weather concepts into a single weather variable.

Event Variable. The third modeling challenge is constructing model variables that capture the impact of demand response programs on historical loads. The basic model variables described above will predict loads under non-event days. To capture the load shed as a result of a load control event it is natural to consider inclusion of a binary variable that takes on a value of 1.0 when an event is called and 0.0 otherwise. The coefficient on this variable should be equal to the kW reduction that occurs in that hour when an event is called.

There are two challenges to this approach. First, not all event days are the same. Some event days occurred during days of extreme temperatures and other events were during days of mild temperatures. This was the case in 2006 because events were triggered when the CA ISO as a system total was facing capacity restrictions. These conditions were driven not just by weather occurring in San Diego, but also the conditions in Northern California and the rest of Southern California. It is plausible that San Diego was experiencing relatively mild weather when the rest of California was facing extremely hot temperatures. The use of a simple binary variable would give you the average load reduction which in the case of extreme hot conditions in San Diego would under forecast the potential for load reduction. Second, because the relatively volatile customer loads it is plausible that the interval data used to estimate the models would imply an increase in loads during control events rather than decreased loads. To control for these effects two steps are taken. First, the Event Binary variable is interacted with hourly temperature data. In this way mild temperature event days can be separated from extremely hot event days. Second, the event days when loads increased due to immeasurable reasons are removed from the analysis. The result is a model that produces forecasts of load reductions that are correlated to the prevailing temperature conditions. That is, hotter days will lead to greater load reductions.

Submitting a Forecast to the CAISO

SDGE is following the guidelines developed by the statewide demand response working group to submit a forecast[3]. Currently, SDGE will submit a demand response forecast in an excel file, via e-mail, to the CAISO before demand response events are triggered. The hourly forecasts are broken out by program

[3] CAISO Demand Response Resource Users Guide, Guide to Participation in MRTU Release 1, Version 3.0, November 29, 2007, California Independent System Operator

and by day-ahead and day-of notification. This is done because each forecast serves as an input into the day-ahead and hour-ahead wholesale energy markets. In each of the wholesale energy markets, the demand response estimates are used to adjust the CAISO's Forecast of CAISO Demand (CFCD). The CAISO will update the CAISO's Forecast of CAISO's Demand (CFCD) before the day-ahead market begins at 10 A.M. and then 75 minutes before each of the hour-ahead markets begin. This adjustment reduces the procurement target for bid-in demand and requires less bid-in supply to meet system requirements.

After each demand response event, SDGE has seven days to provide actual results of demand response achieved to the CAISO. This is done to compare submitted forecasts with actual results and to determine how well the forecasting system is performing. At the end of the calendar year, SDGE will provide a final report for all demand response programs to the CAISO. This will ensure that the data reported to the CAISO will be consistent with what is reported to the California Public Utilities Commission (CPUC) and other regulatory agencies.

Forecast Performance Results

The Demand Response Forecasting System has been used by SDG&E to develop demand response forecasts since May 1, 2008. The summer of 2008 will be the first full demand response season with the forecasting system in place and will give SDG&E valuable feedback on its forecast performance. SDG&E initiated AC Summer Saver events on October 1 and 8, 2008, both between the hours of 2 p.m. through 5 p.m. In Figure 1, the aggregated load shape is presented for customers on a 100% AC Saver cycling program. The "Control" load shape corresponds to AC Saver customers that were not cycled. The "Test" load shape corresponds to the AC Saver customers that had 100% cycling of their air conditioning. The difference between these two shapes provides an ex post estimate of the realized load reduction. The post 5 p.m. jump in loads corresponds to the bounce-back in air conditioning loads after the event period concludes.

The ex post estimated load reduction is compared to the day-ahead load reduction forecast in Figure 2. The day-ahead load reduction forecasts called for a maximum load shed of 8.1 MW during the 2 p.m. to 3 p.m. time window. The ex post estimated maximum load shed is 6.5 MW of load reduction during the time window of 4 p.m. to 5 p.m.

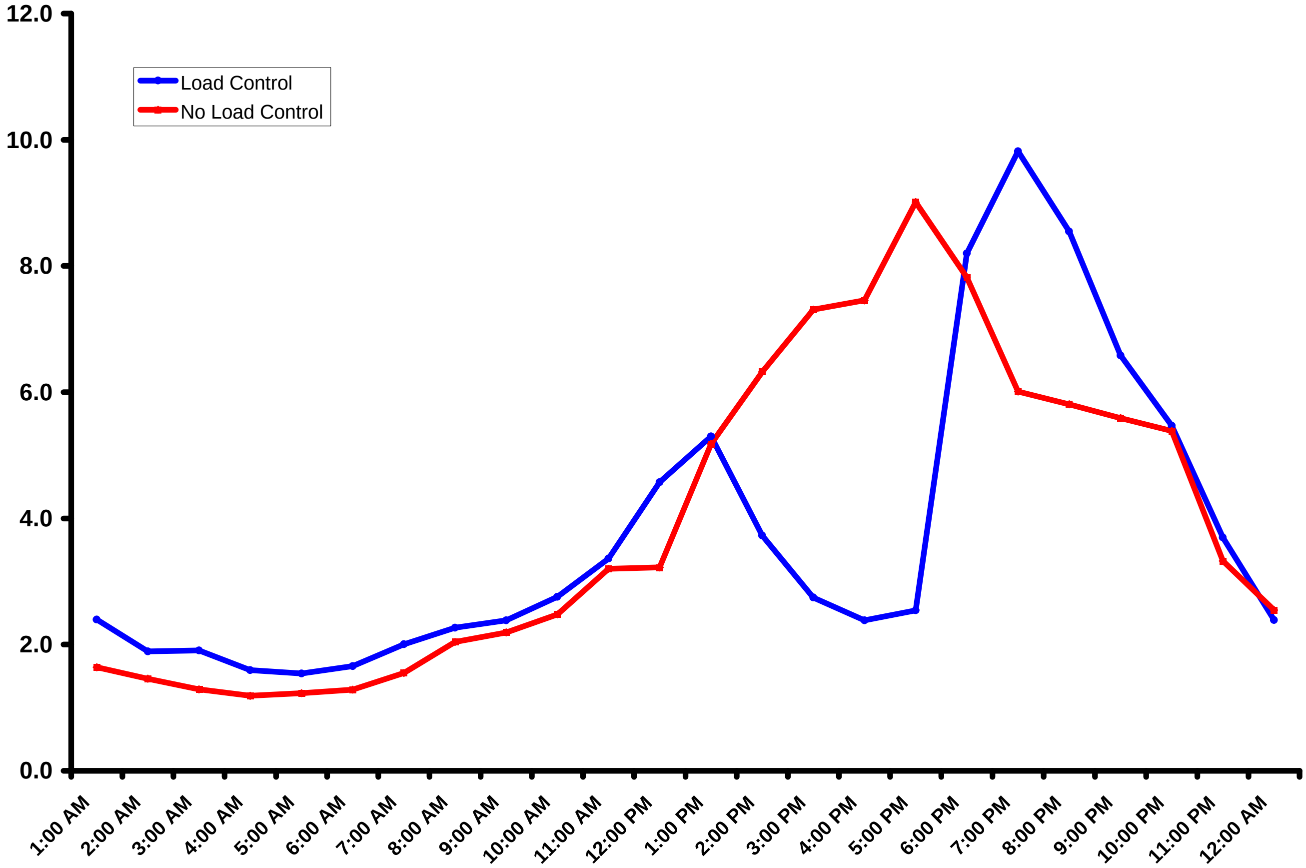

Figure 1. Preliminary Estimates: Load Shapes for Residential Customers on the 100% AC Saver Cycling Program for October 8, 2008

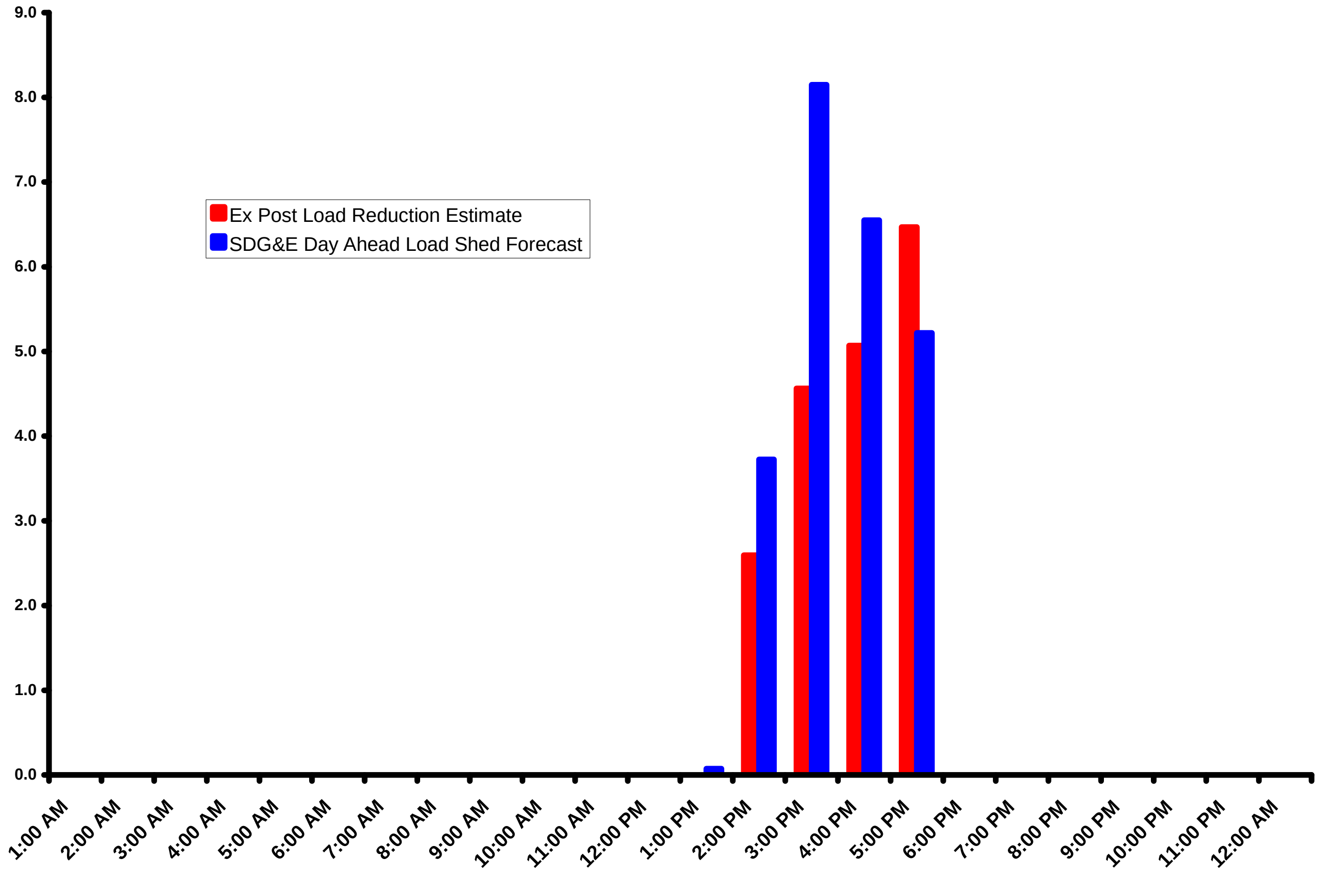

Figure 2. Preliminary Estimates: Forecasted Versus Ex post Estimated Load Reduction for Residential Customers the on 100% AC Saver Cycling Program for October 8, 2008

Conclusions

Demand response load reduction is a viable generation resource if and only if it can be relied on when an event is triggered. This means having the ability to forecast accurately the amount of load reduction is critical to the successful deployment of large-scale demand response programs. SDG&E has taken a major step forward to achieving the goal of accurately forecasting the load shed potential by utilizing a forecasting framework that relies on the same class of statistical forecasting models that are used by system operators to forecast system loads on a balance-of-the-day and next-day basis. The early results suggest this approach promises to deliver the forecast accuracy that is required.

What impact will AMI have on demand response programs? AMI will broaden the footprint of demand response programs in several ways. First, demand response only makes sense when customer loads are measured with an interval meter. The AMI initiatives underway in California will mean every customer's electricity usage will be measured with an interval meter. Second, the interval meters that are to be deployed will contain two-way communication functionality. This means demand response programs like AC saver programs that support central dispatching of air conditioning cycling can be deployed feasibly to many more customers that have air conditioning. For non-cycle based programs, the two-way communication capability of the next generation of smart meters will allow customers to see price signals in real-time via their meter. It is also plausible that forecasts of a customer's load with and without demand response can be pushed to the customer, providing them with valuable information about the benefits of shedding loads. Third, collecting the interval meter reads in virtually real-time will mean system operators will receive valuable feedback on the effectiveness of each demand response event within hours of the event being issued. Finally, deeper penetration of demand response programs into the customer base will improve the accuracy of the forecast models because the volatility of the loads being modeled will average away with larger and larger samples.

If you are a utility contemplating offering demand response to your customers it is important to invest not only in the metering and communication systems required to issue load control events, but also forecasting systems that can project the level of MW reduction that can be expected if an event is called. SDG&E has demonstrated that a state-of-the-art demand response forecasting system is a key component of a successful demand response program.