Highly Volatile-Load Customer Study

for

Southern California Edison, Pacific Gas and Electric Company, and San Diego Gas & Electric

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ABSTRACT

This report documents the results of a statewide highly volatile-load customers (HVLC) study of demand response (DR) customers being undertaken for the three California investor-owned electric utilities ("Joint Utilities"), conducted by Christensen Associates Energy Consulting, LLC (CA Energy Consulting).

The overarching objectives of this exploratory study are too:

- Develop a definition of highly volatile load customers
- Estimate the number of HVLC customers in the IOU's baseline DR programs
- Estimate the MWs contributed by those customers
- Propose a plan for steering HVLC customers towards non-baseline DR programs
- Determine the proportion of DR adjustable baseline customers that exceed the maximum adjustment of 20%.

The context involves the optimization of customers' participation in DR programs that require calculation of baseline loads. One primary issue involves the accuracy of baseline loads calculated for HVLC customers, and the corresponding accuracy of measures of customers' performance during DR events and financial compensation provided for that performance. The study provides a tool that utilities can use to better guide customers to appropriate DR programs given the nature of their typical load patterns. Two statewide programs—the Demand Bidding Program (DBP) and Capacity Bidding Program (CBP) were selected for this element of the analysis, where data for 2009 was used.

A second element of the project involved estimation of *day-of baseline adjustment factors*, and analysis of how the range of those factors varies with key customer characteristics. Data for 2010 from customers enrolled in the three utilities' CBP programs, plus data for SDG&E's Demand Smart Program (DSP), were used in this analysis.

This project has produced a wealth of information on the range of load variability of the customers enrolled in CBP and DBP demand response programs, its association with measures of baseline accuracy and potential errors in DR program credits, and the characteristics of customers who are identified as HVLC customers. Examination of the distributions of load variability for customers in those programs, as measured by the average coefficient of variation (CV) of afternoon loads, indicates that the distributions generally turn up sharply (as do measures of baseline errors) after values of approximately 0.2 to 0.3 (*e.g.*, standard deviations around mean values of afternoon load levels of 20 to 30 percent). Two primary conclusions from the analysis of distributions of load variability are the following:

- The CBP programs generally exhibit smaller percentages of customers with relatively high load variability (*e.g.*, 10 to 20 percent of customers have an average CV greater than 20 to 30%) than do DBP programs, for which as many as 30 to 50 percent of customers may exceed that degree of load variability.

- Distributions of load variability also differ substantially by industry type. *Commercial-type* customers (*e.g.*, retail stores, offices, government buildings) generally display the lowest percentages of highly variable loads. The *first and third industry groups* (*i.e.*, agriculture, mining and construction; and wholesale, transportation and other utilities) show the greatest degrees of load variability. *Manufacturing* customers generally include a majority that display relatively low load variability, but also a substantial portion with high load variability. Finally, where present, a large portion of *School* customers have relatively low load factors and high load variability.

In addition, a simulation exercise designed to examine the effect of load variability on potential errors in program credit payments demonstrated two primary effects of the structure of CBP and DBP credit mechanisms. First, above a relatively low level of load variability, the potential average percentage payment error is relatively insensitive to the degree of load variability. Second, the payment structure limits the effect of even extremely high load variability on the magnitude of average payment errors.

Given these observations we recommend a relatively conservative HVLC criterion of 0.3, or 30 percent in the average coefficient of variation (CV) for non-event-day afternoon loads. We also provide a straightforward spreadsheet tool that may be used to predict the likelihood that a given customer will exceed the HVLC criterion, using data on readily available customer characteristics data such as industry type, size, and load factor (average demand/ maximum demand). Utility staff may use this tool to screen current and potential future DR program enrollees as part of a process for guiding them to the most appropriate DR program or rate.

Using the recommended HVLC criterion, an average of 25 percent of the program enrollees are identified as HVLC, though results differ substantially by utility and program. In particular, the percentages of HVLC customers are generally lower for CBP than for DBP.

Regarding the analysis of *baseline adjustment factors* for CBP and DSP customers in 2010, the study produced information on the frequency with which the current 20 percent adjustment cap was exceeded, along with more detailed information on the full distributions of baseline adjustment factors by utility and program, for both actual and simulated events, and for customers who selected the adjustment option and those that did not. The following are observations on the ranges of baseline adjustments:

- Adjustment factors of *greater* than the 20 percent cap were substantially more frequent than *downward* adjustments of more than 20 percent (32 percent versus 4 percent overall for actual events, for those selecting the adjustment option).
- Adjustment factors exceeding 20 percent were more frequent for the *actual* events compared to the *simulated* for those customers who selected the adjustment option (32 percent overall compared to 15 percent).
- Adjustment factors exceeding 20 percent were somewhat more frequent for customer accounts *choosing the adjustment option* than for those *not choosing* it (*e.g.*, 32 percent overall compared to 24 percent, for the actual events).

EXECUTIVE SUMMARY

This report documents the results of a statewide highly volatile-load customers (HVLC) study of demand response (DR) customers being undertaken for the three California investor-owned electric utilities ("Joint Utilities"), conducted by Christensen Associates Energy Consulting, LLC (CA Energy Consulting). The study has been commissioned to satisfy the directives set forth by the CPUC in Ordering Paragraph (OP) 29 of Decision 09-08-027 dated August 20, 2009:

> 29. Pacific Gas and Electric Company, Southern California Edison Company, and San Diego Gas & Electric Company shall each work with parties to develop a definition of highly variable load customers, and to prepare a report containing that definition along with an estimate of the number of highly variable load customers currently in its baseline demand response programs, and the number of megawatts contributed to the programs by those customers. The report shall propose a plan for steering highly variable load customers towards demand response programs that do not require baseline calculations for settlement purposes. This report shall also include information on the proportion of customers choosing the morning-of adjustment option that reach or exceed the maximum adjustment of 20%, and how often that maximum adjustment is reached.

The overarching objectives of this exploratory study are too:

- Develop a definition of highly volatile load customers
- Estimate the number of HVLC customers in the IOU's baseline DR programs
- Estimate the MWs contributed by those customers
- Propose a plan for steering HVLC customers towards non-baseline DR programs
- Determine the proportion of DR adjustable baseline customers that exceed the maximum adjustment of 20%

The context of the project involves the optimization of customers' participation in demand response (DR) programs that require calculation of baseline loads. One primary issue concerns the accuracy of baseline loads calculated for HVLC customers, and the corresponding accuracy of measures of customers' performance during DR events and financial compensation provided for that performance. The study provides a tool that utilities can use to better guide customers to appropriate DR programs given the nature of their typical load patterns. Two statewide programs—the Demand Bidding Program (DBP) and Capacity Bidding Program (CBP) were selected for this part of the analysis, where data for program-year 2009 were used.

A second part of the project included an assessment of *day-of baseline adjustment factors*, and an analysis of how the range of those factors varies with key customer characteristics. Data for program-year 2010 (though August) from customers enrolled in the three utilities' CBP programs, plus data for SDG&E's Demand Smart Program (DSP), were used in this analysis.

ES.1 Background and Objectives

DBP customers have opportunities to bid load reductions, and CBP customers can have load reductions nominated for event days. The customers receive financial incentive payments that depend on the extent to which they meet those load reduction bids or commitments. Performance (load reduction) is measured as the difference between observed usage during an event and an estimated baseline load level. Through 2009, the baseline calculation method for both programs was the unadjusted 3-in-10 method.[1] Some programs, including DBP and CBP, have converted to a 10-in-10 method, with an option available to enrolled customers to select a *day-of adjustment* to the 10-in-10 baseline, which modifies the event baseline using observed customer usage information in certain pre-event hours of event days.[2] Issues of concern are the accuracy of the baseline methods for customers with highly variable loads, and the number and extent of the magnitude of adjustments that exceed 20% for customers choosing the day-of baseline adjustments.

The primary goals of this study are the following:

1. Develop an agreed-upon definition of HVLC, and then determine the number of such customers currently participating in DBP and CBP, using data for program-year 2009, and calculate the amount and percentage of load and load reductions that those customers contributed during events.
2. Based on the above analysis, develop a straightforward and transparent tool that can be used to identify HVLCs and potentially steer them toward DR programs that do not require baseline calculations, such as critical peak pricing (CPP).
3. Use 2010 program-year data to calculate day-of baseline adjustments for the customer accounts enrolled in CBP at the three utilities, and DSP at SDG&E, and then determine and report the percentage of those customers whose adjustments equal or exceed the maximum adjustment of 20 percent.

ES.2 HVLC Analysis

The first step in the HVLC analysis involved assembling databases for each program that contained customer-level data on the following factors:

1. Industry Group
2. Size (Max kW)
3. Load factor (Average kW / Maximum kW, for June through September)
4. Average CV (Average of the Coefficients of Variation of each customer's loads in hours-ending (HE) 13 – 19 on non-event weekdays)
5. Baseline accuracy (Relative Root Mean-Square Error (RRMSE), and Mean and Median percent error for 10 simulated events on non-event days)
6. Average hourly load impact for the typical event in 2009.

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[1] That is, the baseline load in a particular time period (hour or quarter-hour) is equal to the average in that time period over the three days in the most recent previous ten eligible weekdays (*e.g.,* those that were not themselves event days), which have the greatest energy consumption in the potential event hours.

[2] The adjusted 10-in-10 baseline uses all of the previous ten eligible weekdays to compute an average load; then adjusts that load based on the ratio of the average consumption in the first three of the four hours prior to the event to the average consumption in the same hours on the 10 previous days.

A natural measure of load variability is the *coefficient of variation* (CV) of customers' loads during afternoon hours. CV is a useful statistical measure of relative variability around a mean value, which is equal to the ratio of the *standard deviation* of a data series divided by the *average* value. For example, a CV value of 1.0 implies that the standard deviation is equal in magnitude to the average value, a reasonably wide spread in values. In contrast, a value of 0.10 implies that the standard deviation is only 10 percent of the mean, implying that values are fairly tightly packed around the mean. We calculated the CV of each customer's load for potential event hours (hours-ending 13 through 19) on non-event weekdays during June through September, and then calculated the average of their hourly CVs.[3]

The second step involved producing a number of graphs to explore the relationships between several of the above factors. Figure ES.1 provides an example of these relationships for the case of SCE's 460 CBP customers for whom average hourly load reductions of at least 10 kW were estimated in 2009.[4] The observations in the graph are ordered by values of *average CV*, which are shown by the green triangular symbols that increase gradually from left to right from near zero to 20 percent until about 90 percent of the way across the graph, and then begin to rise sharply.

Measures of unadjusted and adjusted *baseline errors* are shown by the red diamond and pink square-shaped symbols that cluster around the (bold) zero horizontal line near the center of the figure. In this example, there appears to be a positive correlation between the median % errors for unadjusted and adjusted baselines and the average CV (that is, greater baseline errors are associated with greater load variability).

The blue diamond-shaped symbols in the upper portion of the graph represent values of *load factor* (the ratio of average demand to maximum demand), which generally decrease gradually from about 80 percent to 40 percent as the average CV (load variability) increases from left to right. There appears to be a dramatic decrease in load factor for many of the most highly variable customers on the far right of the graph. In this case, 420 out of the total of 460 customer accounts had average CV values of less than 20 to 30 percent and average baseline errors of less than about 10 percent. The average CV values for the customers at the far right rise dramatically, which is an indication of their high variability, along with their estimated baseline errors.

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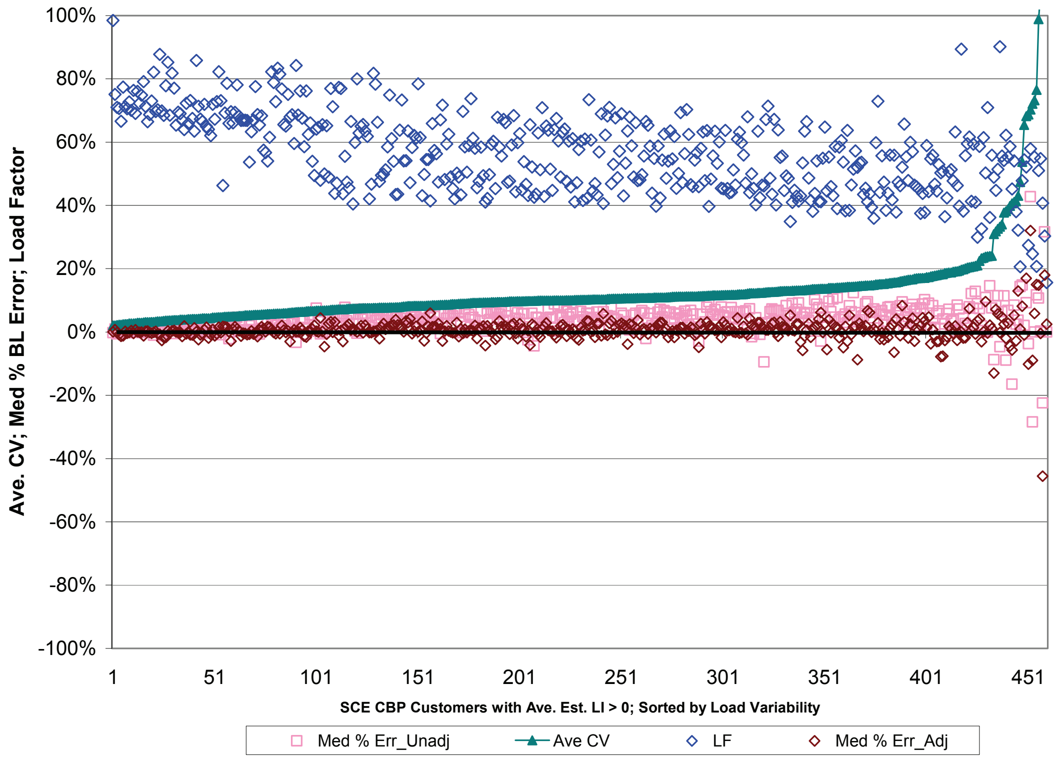
[3] One might expect that load variability due to weather effects on weather-sensitive customers might be an important factor, suggesting a need to adjust those customers' loads for weather differences before calculating the average CV measures. However, the analysis results demonstrate that the three industry groups that would be expected to be most weather sensitive, which include retail stores and office buildings, actually show relatively low load variability and high baseline accuracy.

[4] The analyses in the body of the report for CBP examine both customers for whom load impacts were estimated in 2009 and those for whom estimated load impacts were zero or negative (load increases). For DBP, separate figures were provided for bidders and non-bidders. The intent was to examine the potential effect on estimated program load impacts if certain HVLC customers were moved to a different program.

Figure ES.1. Load Variability, Baseline Errors and Load Factor – *SCE CBP (Customers with Estimated Load Reductions)*



The study results for the CBP and DBP programs, which in some cases were differentiated by industry type, suggest a number of conclusions regarding the load variability of the CBP and DBP customer accounts, including the following:

- There is a direct relationship between a detailed measure of inherent *load variability* such as the average CV of afternoon loads and estimates of *baseline accuracy* (for both unadjusted and adjusted baselines).
- More easily obtained measures of load variability, such as load factor, are directly related to the more detailed average CV measure, however the relationship is not extremely tight. For example, customers with relatively low load factors of around 40 percent are *likely* to have a relatively high average CV, but some can have CVs of less than 20%.
- Customer accounts in both programs at all the utilities show distributions of load variability characterized by relatively large percentages of customers with relatively low load variability (*e.g.*, average CV less than 20 to 30%), although the distributions vary by program.
- Distributions of load variability for CBP customer accounts generally exhibit smaller percentages of customers with relatively high load variability (*e.g.*, 10 to 20 percent of customers have an average CV greater than 20%) than do DBP customer accounts, for which as many as 30 to 50 percent of customers may exceed that degree of load variability.
- Distributions of load variability also differ substantially by industry type, with *commercial-type* customers (*e.g.*, retail stores, offices, government buildings)

generally displaying much lower percentages of highly variable loads, and the *first and third industry groups* (*i.e.*, agriculture, mining and construction; and wholesale, transportation and other utilities) showing much greater degrees of load variability. *Manufacturing* customers generally include a range of those with relatively low variability and those exhibiting high variability.

ES.3 HVLC Definition and Screening Tool

In addition to the above findings on distributions of load variability, a simulation exercise designed to examine the effect of load variability on potential errors in program credit payments demonstrated two primary effects of the structure of CBP and DBP credit mechanisms. First, above a relatively low level of load variability, the potential average percentage payment error is relatively insensitive to the degree of load variability. Second, the payment structure limits the effect of even extremely high load variability on the magnitude of average payment errors.

Given these observations we recommend a relatively conservative HVLC criterion of 0.3, or 30 percent in the average coefficient of variation (CV) for non-event-day afternoon loads. We also provide a straightforward spreadsheet tool that may be used to predict the likelihood that a given customer will exceed the HVLC criterion, using data on readily available customer characteristics data such as industry type, size, and load factor (average demand/ maximum demand). Utility staff may use this tool to screen current and potential future DR program enrollees as part of a process for guiding them to the most appropriate DR program or rate.

Table ES.1 shows the number of customer accounts, average size, and average hourly load impacts for the average, or typical event, that were estimated in the 2009 load impact evaluations for the utilities' DR programs listed. Using the HVLC criterion recommended of an average CV of 0.3 or greater, the numbers of enrolled customers that are identified as HVLC average 25 percent of the total, though results differ substantially by utility and program. Average maximum demand (customer size) is roughly comparable between the HLVC and non-HVLC groups, with the exception of SCE CBP and SDG&E CBP.[5] Overall, the HVLC customer accounts account for 25 percent of the total estimated average hourly load impacts for CBP and DBP in 2009. Again, results differ substantially across programs, with HVLC customers in the DBP programs accounting for the largest portions of estimated load impacts (see last column in Table ES.1).

[5] One of SDG&E's CBP customers identified as HVLC was a very large customer, which increased the average size for HVLC substantially.

Table ES.1. Number of CBP and DBP Customer Accounts, Their Average Size, and Average Hourly Load Impacts (2009) – *HVLC and Non-HVLC*

		# of Customers			Average Maximum Demand (kW)		2009 Load Impacts (MW)		
Utility	Program	Non-HVLC	HVLC	% HVLC	Non-HVLC	HVLC	Non-HVLC	HVLC	% HVLC
PG&E	CBP	715	243	25%	347	287	32.9	7.6	19%
	DBP	729	287	28%	1,358	1,298	69.3	20.2	23%
SCE	CBP	591	44	7%	283	591	24.0	2.4	9%
	DBP	202	210	51%	1,725	1,330	12.9	18.9	60%
SDG&E	CBP	225	22	9%	308	1,155	13.5	2.4	15%
	Total	2,462	806		741	959	152.7	51.6	
	Shares	75%	25%				75%	25%	

Table ES.2 shows that the average load factor of HVLC customers is substantially lower than that of non-HVLC customers (32 percent compared to 59 percent, on average, across all programs). The average baseline error (as measured by the RRMSE, or U-Statistic) of HVLC customers is substantially higher than that of non-HVLC customers (48 percent compared to 8 percent overall).

As noted above, differences in baseline error do not translate directly to percentage credit payment errors, as the customer incentives vary by program type. For DBP, the incentive payments are based solely on energy performance during events, so the percent payment errors for HVLC customers with high baseline errors are substantially greater than those for non-HVLC. The baseline errors for HVLC customers in the CBP do not necessarily affect incentives as greatly, due to the split of incentives between energy performance during events that are tied to the baseline, and capacity "standby" payments that are provided for CBP even if no events are called. The relatively strong restrictions on performance payments of the CBP capacity credits during events also act as a disincentive for poor performance, with most CBP participants working within an aggregated group which tends to mute individual underperformance.

Table ES.2. Average Load Factors, Baseline Errors, and Average % Credit Payment Errors – *HVLC and Non-HVLC*

		Load Factor		Baseline Error (RRMSE)		Average % Credit Payment Error	
Utility	Program	Non-HVLC	HVLC	Non-HVLC	HVLC	Non-HVLC	HVLC
PG&E	CBP	56%	31%	9%	61%	-51%	-67%
	DBP	61%	33%	9%	40%	-19%	-44%
SCE	CBP	61%	43%	5%	90%	-48%	-61%
	DBP	60%	31%	10%	37%	-6%	-36%
SDG&E	CBP	59%	27%	7%	40%	-41%	-70%
	Total	59%	32%	8%	48%	-36%	-50%

Defining the HVLC criterion on the basis of the average CV threshold metric of 0.3 does not imply, however, that the utilities need to calculate individual CV values for all of their potential and existing DR program customers in order to screen for HVLC. As a screening tool, we developed a simple spreadsheet model for identifying customers who meet the HVLC criterion by estimating a logit regression model that predicts the likelihood of meeting the HVLC criterion based on a short list of readily available customer characteristics. The model's coefficients confirm the patterns in the load variability analysis described above. That is, load factor and industry type are the most important predictors; for example, low load factors imply higher likelihood of HVLC, and membership in the commercial-type industries implies lower likelihood of HVLC.

ES.4 Analysis of Baseline Adjustment Factors

The objectives of this portion of the study include: 1) to determine the portion of customers whose day-of adjustment factors for their settlement baseline reach or exceed the 20 percent adjustment cap (differentiating between customers who selected the adjustment baseline and those that did not), and 2) to measure how often that cap is exceeded for each customer. The utilities offered the use of data from the 2010 program year (through August) for the CBP programs, plus SDG&E's DSP.

We first used customer-level hourly interval load data, along with customer enrollment and event data, to calculate the 10-in-10 baseline for each CBP and DSP customer and event at each utility. We then computed the *day-of adjustment factors* for each customer and event at each utility using the ratio of the average load on the event day to the average load in the 10-in-10 baseline, averaging over the 4^{th}, 3^{rd}, and 2^{nd} hour preceding the start of the event, while accounting for each customer's program type and event start time.

Adjustment factors were computed for each event day, as well as for an additional series of simulated-event days. Seven simulated event days were selected for each program from the days of highest system load in the summer of 2009 that were not called as CBP or DBP event days. In most cases, actual events were called on at least the three or four highest-load days and in some cases more (*e.g.*, the nine highest-load days for SDG&E's day-of CBP). As a result, simulated event days typically occurred on days of lower system load and average temperatures than actual event days. Differences between adjustment factors on simulated-event days and on actual event days could potentially result from two primary factors. One is that on actual events some customers may take pre-event actions such as pre-cooling that may affect their day-of adjustment factors. Another is that weather conditions are generally more severe on the actual event days than on the simulated event days, which could result in higher day-of adjustment factors than for simulated events.

Table ES.3 provides overall results of this analysis to assess the extent to which baseline adjustment caps were exceeded. It first shows the percentage of CBP customers who selected the adjusted baseline option for each of the three utilities[6] (first row) and then summarizes the following three results for those customers, for both actual and simulated events:

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[6] SDG&E's DSP did not offer adjusted baselines in 2010. However, DSP customers' baseline adjustment factors were calculated for the simulated events, and are reported below.

- The percentage of those customer accounts whose baseline adjustment exceeded the 20 percent cap for at least one event (second row);
- The percentage of customer-events (*i.e.*, the number of customers times the number of events in which they participated) in which the 20 percent cap was exceeded by a customer for an event (third row); and
- The average percent of events per customer for those customers for which the baseline adjustment exceeded the 20 percent cap at least once (last row).

From 36 to 73 percent of customers across the three programs selected the day-of adjustment option for their settlement baselines. Of those customers, more than half experienced adjustments that exceeded the 20 percent cap for at least one actual event, and somewhat fewer reached the cap on the simulated events. Overall, the adjustments for about 30 to 40 percent of all customer-events for those customers selecting the adjustment option exceeded the 20 percent cap, while 20 percent or less did so for the simulated events. Finally, for those customers whose adjustments exceeded the cap at least once, they did so for 50 to 60 percent of the actual events, and 30 to 40 percent of the simulated events.

Table ES.3. Overall Percentages of Occurrences of Exceeding 20 Percent Cap

	PG&E CBP		SCE CBP		SDG&E CBP	
	Actual	Sim	Actual	Sim	Actual	Sim
% of Customers selecting BL adjustment option	36%	36%	47%	47%	73%	73%
% of Customers who (ever) exceeded 20% cap	56%	42%	55%	45%	55%	38%
% of Customer-events that exceeded cap	36%	13%	38%	20%	29%	14%
Ave. % of evts. per cust. where cap exceeded	63%	31%	69%	44%	52%	36%

Table ES.4 provides additional detail on the range of baseline adjustments for both those customer accounts that did and did not select the adjusted baseline option, and for both the actual program events and the simulated events. Results for DSP are shown in the lower portion of the table.[7] The following are observations on those ranges:

- Adjustment factors of *greater* than the 20 percent cap were substantially more frequent than *downward* adjustments of more than 20 percent (32 percent versus 4 percent overall for actual events, for those selecting the adjustment option).
- Adjustment factors exceeding 20 percent were more frequent for the *actual* events compared to the *simulated*, or pseudo-events, for those customers who selected the adjustment option (32 percent overall compared to 15 percent).
- Adjustment factors exceeding 20 percent were somewhat more frequent for customer accounts *choosing the adjustment option* than for those *not choosing* it (*e.g.*, 32 percent overall compared to 24 percent, for the actual events).
- Adjustment factors exceeding 20 percent for DSP customers were considerably more frequent for both actual and simulated events than those for CBP customers in total (*e.g.*, 43 percent versus 24 percent for actual events).

[7] The actual program baseline for DSP in 2010 was the unadjusted 3-in-10 method. However, the day-of adjustment results in the table were calculated using the 10-in-10 baseline.

Table ES.4. Distributions of Day-of Baseline Adjustment Factors by Utility, Event Type, and Choice of Adjustment Option – *CBP and DSP*

		Event	Adjustment	-20% to +20% BL Adjustment		
Utility	Program	Type	Option	Below	Within	Above
All	All	Actual	Yes	4%	64%	32%
PGE	CBP	Actual	Yes	9%	56%	36%
SCE	CBP	Actual	Yes	1%	60%	38%
SDGE	CBP	Actual	Yes	3%	68%	29%
All	All	Actual	No	9%	67%	24%
PGE	CBP	Actual	No	12%	60%	28%
SCE	CBP	Actual	No	1%	79%	20%
SDGE	CBP	Actual	No	12%	71%	17%
All	All	Pseudo	Yes	7%	79%	15%
PGE	CBP	Pseudo	Yes	9%	78%	13%
SCE	CBP	Pseudo	Yes	7%	74%	20%
SDGE	CBP	Pseudo	Yes	4%	82%	14%
All	All	Pseudo	No	8%	79%	13%
PGE	CBP	Pseudo	No	10%	79%	11%
SCE	CBP	Pseudo	No	1%	83%	16%
SDGE	CBP	Pseudo	No	11%	76%	13%

		Event	Adjustment	-20% to +20% BL Adjustment		
Utility	Program	Type	Option	Below	Within	Above
SDGE	DSP	Actual	No	13%	44%	43%
SDGE	DSP	Pseudo	No	15%	55%	30%

ES.5 Conclusions and Recommendations

This project has produced a wealth of information on the range of load variability of the customers enrolled in CBP and DBP demand response programs, its association with measures of baseline accuracy and potential errors in DR program credits, and the characteristics of customers who are identified as HVLC customers. Examination of the distributions of load variability for those programs, as measured by the average coefficient of variation (CV) of afternoon loads, indicates that the distributions generally turn up sharply (as do measures of baseline errors) after values of approximately 0.2 to 0.3 (*e.g.*, standard deviations around mean values of afternoon load levels of 20 to 30 percent). Two primary conclusions from the analysis of distributions of load variability are the following:

- The CBP programs generally exhibit smaller percentages of customers with relatively high load variability (*e.g.*, 10 to 20 percent of customers have an average CV greater than 20 to 30%) than do DBP programs, for which as many as 30 to 50 percent of customers may exceed that degree of load variability.
- Distributions of load variability also differ substantially by industry type. *Commercial-type* customers (*e.g.*, retail stores, offices, government buildings) generally display the lowest percentages of highly variable loads. The *first and third industry groups* (*i.e.*, agriculture, mining and construction; and wholesale, transportation and other utilities) show the greatest degrees of load variability. *Manufacturing* customers generally include a majority that display relatively low

load variability, but also a substantial portion with high load variability. Finally, where present, a large portion of *School* customers have relatively low load factors and high load variability.

In addition, a simulation exercise designed to examine the effect of load variability on potential errors in program credit payments for load reductions demonstrated two primary effects of the structure of CBP and DBP credit mechanisms. First, above a relatively low level of load variability, the potential average percentage payment error is relatively insensitive to the degree of load variability. Second, the payment structure limits the effect of even extremely high load variability on the magnitude of average payment errors.

Given these observations we recommend a relatively conservative HVLC criterion of an average coefficient of variation (CV) for non-event-day afternoon loads in excess of 0.3, or 30 percent. We also provide a straightforward spreadsheet tool that may be used to predict the likelihood that a given customer will exceed the HVLC criterion, using data on readily available customer characteristics data such as industry type, size, and load factor (average demand/ maximum demand). Utility staff plan to use this tool to screen current and potential future DR program enrollees as part of a process for steering HVLC customers towards non-baseline DR programs.

Using the recommended HVLC criterion, an average of 25 percent of the program enrollees are identified as HVLC, though results differ substantially by utility and program. In particular, the percentages of HVLC customers are generally lower for CBP than for DBP.

Regarding the analysis of baseline adjustment factors for CBP and DSP customers in 2010, the study produced information on the frequency with which the current 20 percent adjustment cap was exceeded, along with more detailed information on the full distributions of baseline adjustment factors by utility and program, for both actual and simulated events, and for customers who selected the adjustment option and those that did not. The following are observations on the ranges of baseline adjustments:

- Adjustment factors of *greater* than the 20 percent cap were substantially more frequent than *downward* adjustments of more than 20 percent (32 percent versus 4 percent overall for actual events, for those selecting the adjustment option).
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1. INTRODUCTION AND KEY ISSUES

This report documents the results of a statewide study of highly volatile-load customers (HVLC) of the three California investor-owned electric utilities ("Joint Utilities"), conducted by Christensen Associates Energy Consulting, LLC (CA Energy Consulting). The context involves these customers' participation in demand response (DR) programs that require calculation of baseline loads. One primary issue involves the accuracy of baseline loads calculated for HVLC customers, and the corresponding accuracy of measures of customers' performance during DR events and financial compensation provided for that performance. The utilities wanted a tool that they can use to better guide customers to appropriate DR programs given the nature of their typical load patterns. Two statewide programs—the Demand Bidding Program (DBP) and Capacity Bidding Program (CBP) were selected for this element of the analysis, where data for 2009 will be used.

A second element of the project involved estimation of *day-of baseline adjustment factors*, and analysis of how the range of those factors varies with key customer characteristics. Data for 2010 from customers enrolled in the three utilities' CBP programs, plus data for SDG&E's Demand Smart program (DSP), were used in this analysis.

The study has been conducted under the guidance of a sub-committee of the Demand Response Measurement and Evaluation Committee (DRMEC), which consists of representatives of the Joint Utilities, the California Public Utilities Commission (CPUC), and the California Energy Commission (CEC). Southern California Edison (SCE) will manage the project.

1.1 Background

Customers enrolled in DBP and CBP have opportunities to bid load reductions (DBP), or have load reductions nominated (CBP) for event days. Customers receive financial incentive payments that depend on the extent to which they meet those load reduction bids/commitments. Performance is measured relative to a baseline load level. Through 2009, the baseline method for both programs was the unadjusted 3-in-10 method.[8] Some programs, including DBP and CBP, have converted to a 10-in-10 method, with an option available to enrolled customers to select a *day-of adjustment* to the 10-in-10 baseline, which is calculated using usage information in certain pre-event hours of event days.[9] Issues of concern are the accuracy of the baseline methods for customers with highly variable loads, and the magnitude of the day-of baseline adjustments.

[8] That is, the baseline load in a particular time period (hour or quarter-hour) is equal to the average in that time period over the three days in the most recent previous ten eligible weekdays (*e.g.,* those that were not themselves event days), which have the greatest energy consumption in the potential event hours.

[9] The adjusted 10-in-10 baseline uses all of the previous ten eligible weekdays to compute an average load; then adjusts that load based on the ratio of the average consumption in the first three of the four hours prior to the event to the average consumption in the same hours on the 10 previous days.

1.2 Scope and objectives

The primary goals of this study are the following:

1. Develop an agreed-upon definition of HVLC, and then determine the number of such customers currently participating in DBP and CBP, using data for program-year 2009, and calculate the amount and percentage of load and load reductions that those customers contributed during events.
2. Based on the above analysis, develop a straightforward and transparent tool that can be used to identify HVLCs and potentially steer them toward DR programs that do not require baseline calculations, such as critical peak pricing (CPP).
3. Use 2010 program-year data to calculate day-of baseline adjustments for the customer accounts enrolled in CBP at the three utilities, and DSP at SDG&E, and then determine and report the percentage of those customers whose adjustments equal or exceed the maximum adjustment of 20 percent.

1.3 Road Map

In the remainder of this report, Section 2 provides a series of graphs illustrating relationships between customer-level measures of load variability, baseline accuracy and load impacts, which provide background information on potential HVLC criteria. Section 3 explores potential effects of load variability on errors in DR payments and credits, provides a recommended HVLC criterion, and summarizes the characteristics of customers identified as HVLC. Section 4 summarizes information on distributions of day-of baseline adjustment factors for CBP and DSP customers in 2010, and indicates how often the adjustments exceed the 20 percent adjustment cap. Section 5 provides conclusions and recommendations.

2. REVIEW OF LOAD VARIABILITY AND BASELINE ACCURACY

This section provides a number of graphs that serve as an exploratory analysis of the relationship between load variability, baseline accuracy, and estimates of program load impacts. These results provide useful information on their own in the form of insights into these relationships. They also provide motivation for the analysis in Section 3 to develop a recommended HVLC criterion and a tool for identifying HVLC customers. Readers interested primarily in the HVLC criterion and analysis tool may wish to skip this section.

2.1 Data Collection and Validation

The HVLC study required substantial amounts of customer-level interval load data for each of the DBP and CBP programs. However, CA Energy Consulting had previously obtained all of the customer characteristics, load data and program data needed to address the first two objectives of the study in the course of DBP and CBP impact evaluations for program-year 2009. Thus, no additional data collection was necessary.

2.2 Alternative Measures of Load Variability

An initial exploratory analysis was undertaken involving two main steps: 1) assemble data and calculate various load statistics; 2) produce graphs showing relationships between alternative measures of load-variability, baseline accuracy, and load impacts.

Statistics on baseline accuracy (for the unadjusted and adjusted 10-in-10 baselines) are included in the analysis because a principle factor of interest in developing an HVLC criterion is the ultimate impact of load variability on accuracy of baseline measurement.

2.2.1 Database development

The first step in the analysis involved assembling databases for each program that contain customer-level data on the following factors:

- NAICS/SIC code
- Industry Group
- Size (Max kW)
- Load factor (Average kW / Maximum kW, for June through September)
- Average CV (Average of the Coefficients of Variation of the loads in HE 13 – 19 on non-event weekdays)
- Baseline accuracy (RRMSE, and Mean and Median percent error for 10 simulated events on non-event days)

2.2.2 Relationship between different measures of load variability

The second step involved producing a number of graphs to explore relationships between several of the above factors. One of the first issues examined was alternative measures of load variability. A natural measure is the coefficient of variation (CV) of customers' loads during afternoon hours. CV is a useful statistical measure of relative variability around a mean value, which is equal to the ratio of the *standard deviation* of a data series divided by the *average* value. For example, a CV equal to 1.0 implies that the standard deviation is equal in magnitude to the average value, a reasonably wide spread in values. In contrast, a value of 0.1 implies that the standard deviation is only 10 percent of the mean, implying that values are fairly tightly packed around the mean. We calculated the CV of each customer's load for potential event hours (hours-ending 13 through 19) on non-event weekdays during June through September, and then calculated the average of their hourly CVs.[10]

While the average CV of afternoon loads, calculated using interval load data, may be the most appropriate measure of load variability, the utilities are interested in a measure that may be conveniently calculated from available customer characteristics and monthly billing data alone. Thus, we also examined customers' *load factor* (LF), equal to average demand divided by maximum demand. Due to lack of consistency in the available billing data across the utilities and programs, we calculated load factors directly from the available hourly interval data, for June through September. In practice, the utilities' billing data may be used to calculate comparable LF values.

Figures 2.1 and 2.2 illustrate the relationship between LF and average CV for all of the customers enrolled in PG&E's DBP and CBP programs. There is a definite negative

[10] One might expect that load variability due to weather effects on weather-sensitive customers might be an important factor, suggesting a need to adjust those customers' loads for weather differences before calculating the average CV measures. However, the analysis results demonstrate that the three industry groups that would be expected to be most weather sensitive, which include retail stores and office buildings, actually show relatively low load variability and high baseline accuracy.

relationship between the two variables in both figures; that is, *higher* load factors are associated with *smaller* average CVs of load. There is a relatively high density of average CV values that are less than 0.2. However, these span a relatively wide band of LF values ranging from approximately 0.3 to 0.9. Thus, while LF is clearly an indicator of load variability, further analysis is required to determine its usefulness in conjunction with other information.

Figure 2.1. Relationship between Load Factor and Average CV – *PGE DBP*

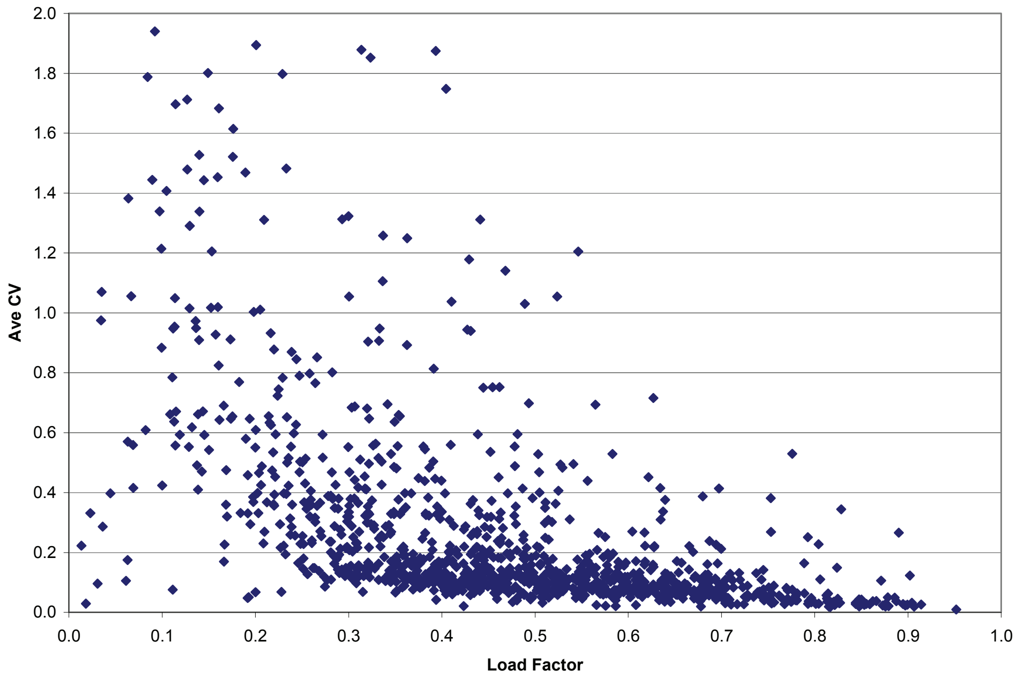
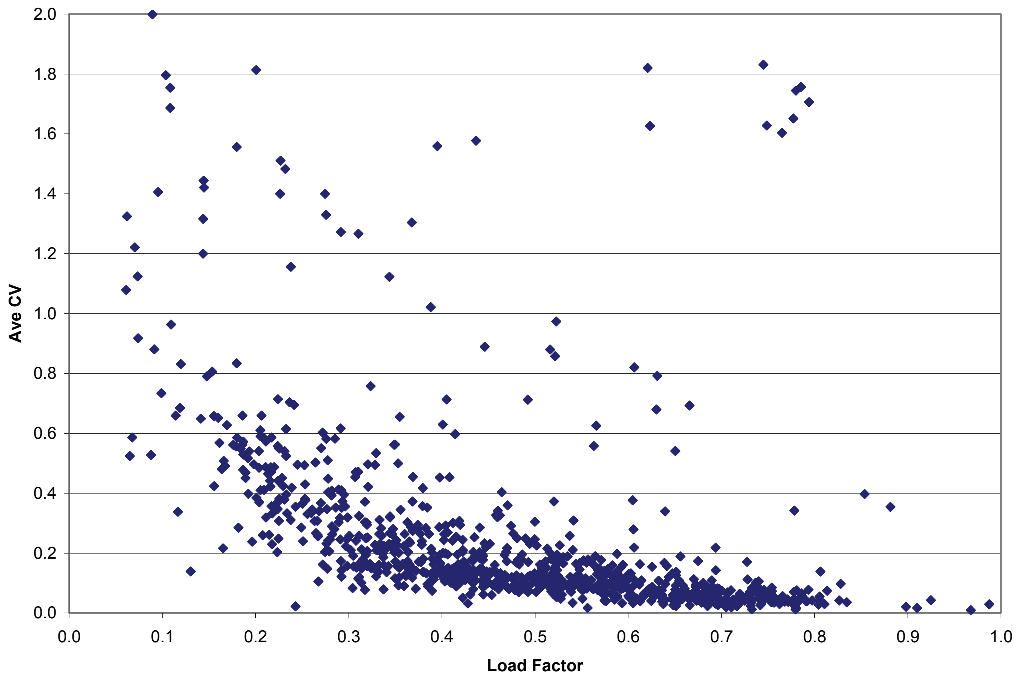


Figure 2.2. Relationship between Load Factor and Average CV – *PGE CBP*



2.3 Load variability and baseline accuracy

The utilities are primarily interested in the relationship between load variability and baseline accuracy. Thus, we now add two measures of *baseline accuracy* – the Relative Root Mean Square Error (RRMSE)[11] for unadjusted and adjusted 10-in10 baselines – to the above two figures, producing Figures 2.3 and 2.4, for which the vertical axis is now restricted to values between zero and 1.0. Figures 2.5 through 2.7 contain similar data for SCE's DBP and CBP customers, and SDG&E's CBP customers respectively. All of the figures display similar patterns, although those for CBP customers appear to contain fewer customers with high CV values (*e.g.*, greater than 0.4) or very low load factors (*e.g.*, less than 0.2). Several other patterns are evident in the figures, including the following:

- A number of the values that indicate accuracy of the *adjusted* baseline (square symbols in pink color) lie below the bulk of the values for the *unadjusted* baseline (open triangle symbols), reflecting the typical finding that the day-of adjustments improve baseline accuracy.
- The indicators of baseline accuracy for both baseline types are largely correlated with the Average CV measure of load variability; there is large dense area of points below 0.2 on the vertical axis, indicating relative baseline errors of less than 20 percent and average CV values of less than 0.2.

[11] RRMSE provides a normalized measure of the difference between two series, in this case "actual" and "estimated" baseline loads. RRMSE is calculated as the square root of the sum of squared differences between the actual and estimated baselines (during potential event hours), divided by the square root of the sum of squared (actual) baseline values. Thus, RRMSE produces values in units of fractions, or percentages, since it essentially represents the ratio of the average baseline error (accounting for both positive and negative errors) and average baseline load level.

- As indicated above, the bulk of these values lie between load factor values of 0.3 to 0.9 on the horizontal axis, although the trend is for less load variability and greater baseline accuracy as the load factors increase from left to right.

Figure 2.3. Relationship between Load Factor, Average CV and Baseline Accuracy – *PGE DBP*

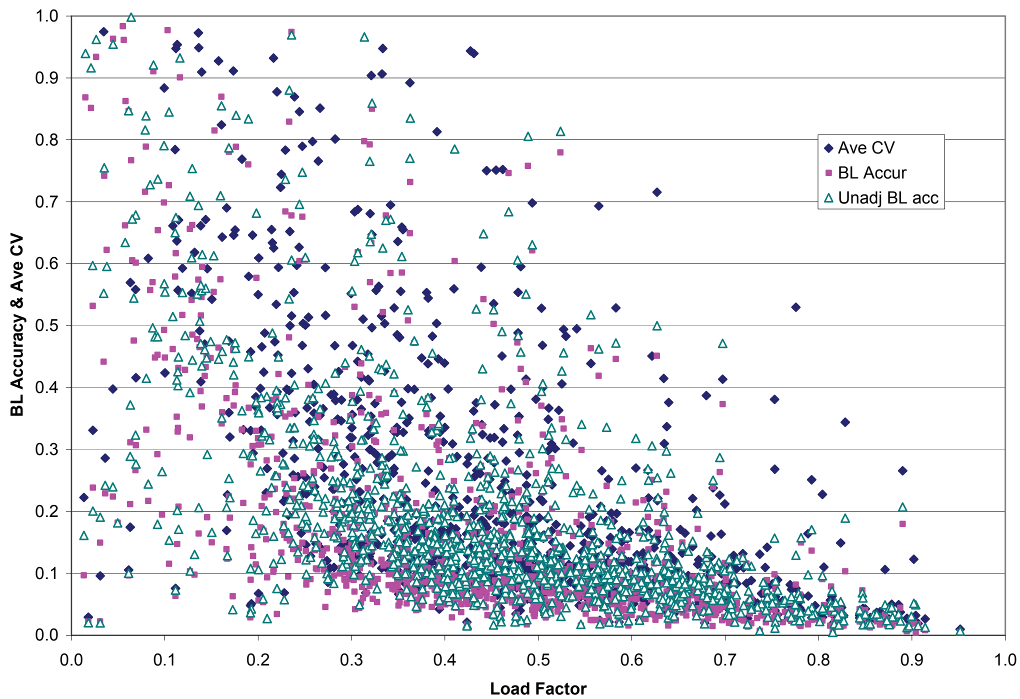


Figure 2.4. Relationship between Load Factor, Average CV and Baseline Accuracy – *PGE CBP*

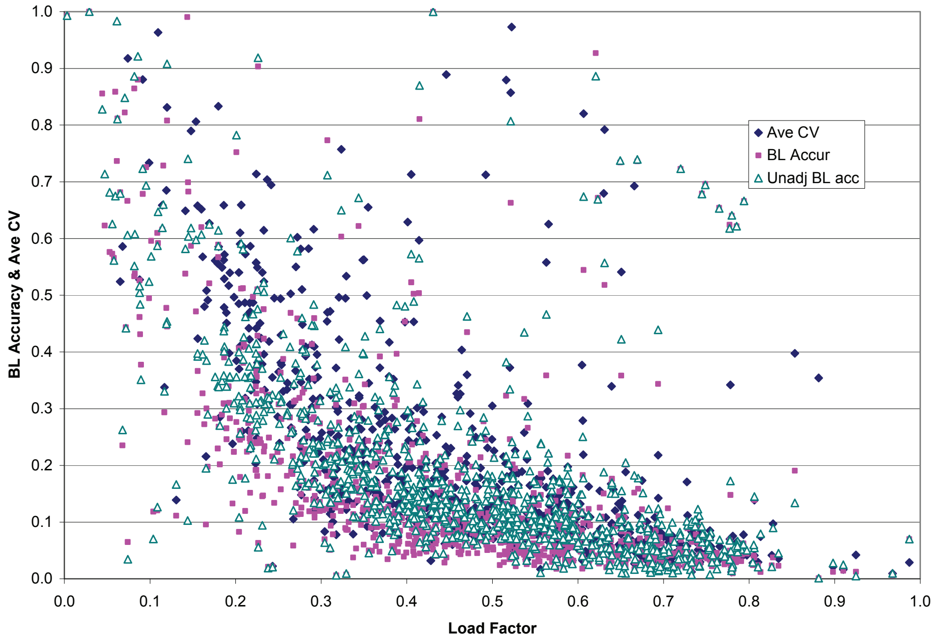


Figure 2.5. Relationship between Load Factor, Average CV and Baseline Accuracy – *SCE DBP*

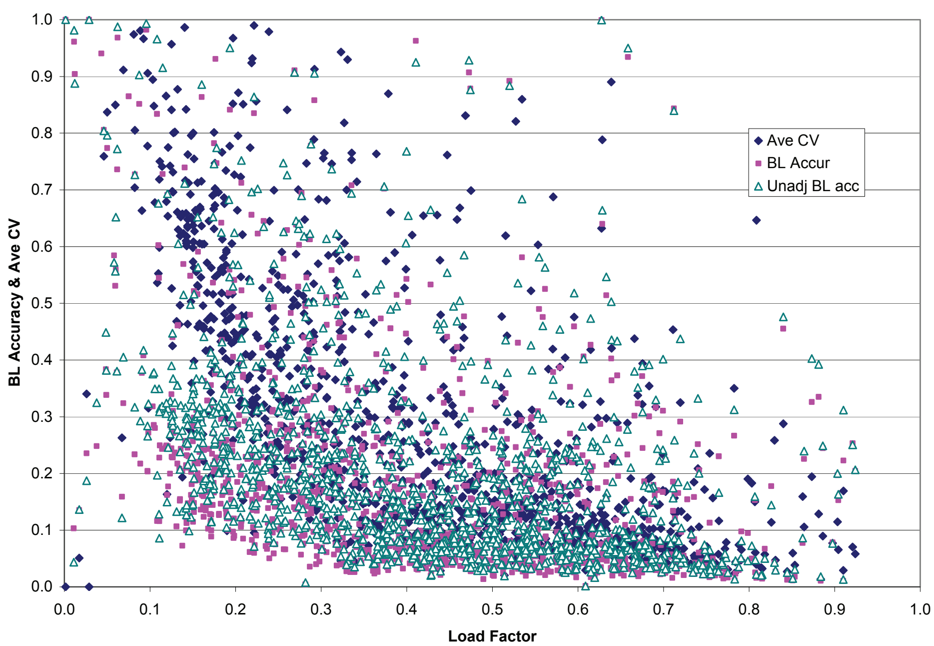


Figure 2.6. Relationship between Load Factor, Average CV and Baseline Accuracy – *SCE CBP*

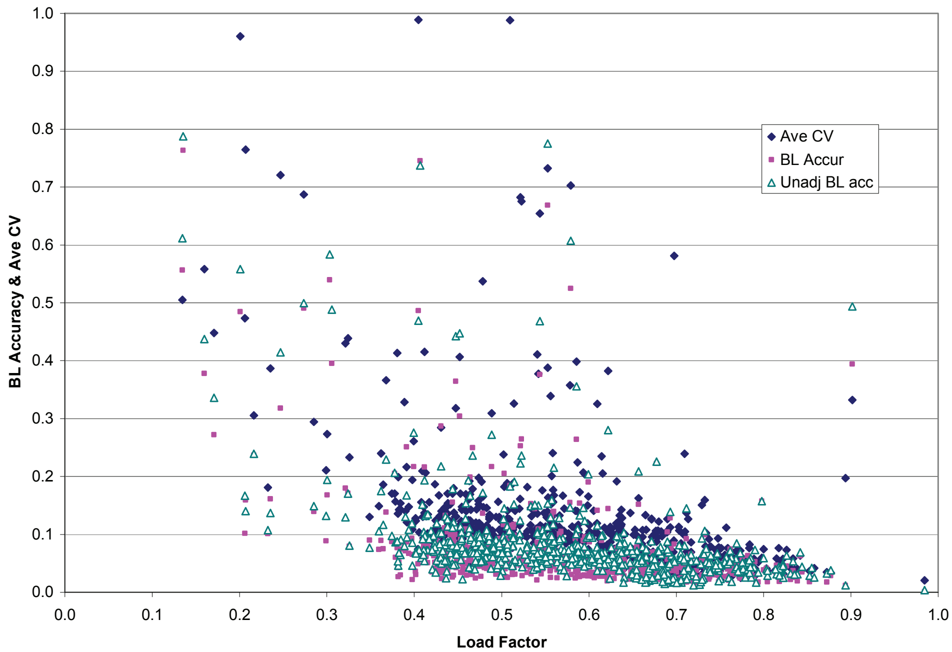
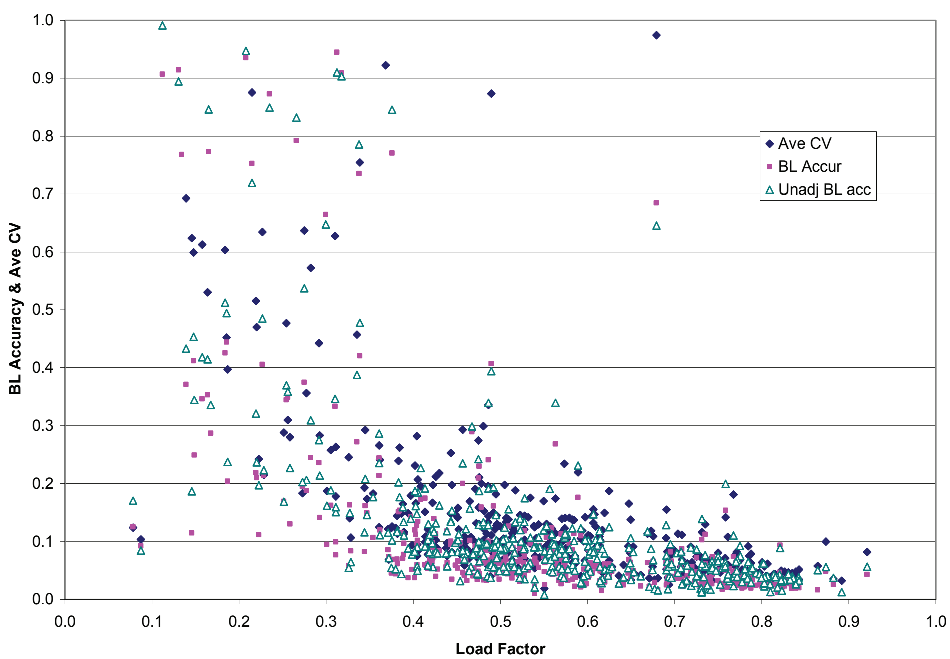


Figure 2.7. Relationship between Load Factor, Average CV and Baseline Accuracy – *SDG&E CBP*



2.3.1 Load variability and baseline accuracy by industry type

The above figures report values for *all* customers enrolled in the programs. It is also of interest to examine how load variability and baseline accuracy differ by industry type. Table 2.1 indicates the standard industry groups and the corresponding North American Industry Classification System (NAICS) codes.[12]

Table 2.1: Industry Group Definition

Industry Groups	NAICS Codes
1. Agriculture, Mining & Construction	11, 21, 23
2. Manufacturing	31 - 33
3. Wholesale, Transport, other Utilities	22, 42, 48 - 49
4. Retail stores	44 - 45
5. Offices, Hotels, Health, Services	51 - 56, 62, 72
6. Schools	61
7. Entertainment, Other Services, Government	71, 81, 92
8. Other/Unknown	

To provide reference points for the HVLC results shown in Section 3 below, Tables 2.2 and 2.3 summarize customer enrollment in each program that is included in this HVLC study, by industry type, in terms of numbers of customer accounts (*i.e.*, service account ID, or SAID) and maximum demand (MW). Table 2.2 shows numbers of customers and maximum demand for the CBP programs, while Table 2.3 shows comparable values for the two DBP programs.

Table 2.2: Enrolled Customers and Load, by Industry Group – *CBP*

Industry Type	CBP Enrollment			Sum of Max. Dem. (MW)		
	PG&E	SCE	SDG&E	PG&E	SCE	SDG&E
1. Agriculture, Mining & Construction	38	2		37.8	0.6	0.0
2. Manufacturing	74	20	38	50.0	8.8	25.1
3. Wholesale, Transport, other Utilities	70	25	33	19.1	9.1	13.8
4. Retail stores	297	566	190	75.0	159.0	53.0
5. Offices, Hotels, Health, Services	229	63	126	47.4	28.7	45.6
6. Schools	67	0	7	37.4	0.0	23.2
7. Entertainment, Other Services, Gov't	122	4	37	13.0	1.5	7.2
8. Other/Unknown	15			1.7	0.0	0.0
Total	912	680	431	281.6	207.8	168.0

[12] SCE provided SIC codes in place of NAICS codes. The industry groups were therefore defined according the following SIC codes: 1 = under 2000; 2 = 2000 to 3999; 3 = 4000 to 5199; 4 = 5200 to 5999; 5 = 6000 to 8199; 6 = 8200 to 8299; 7 = 8300 and higher.

Table 2.3: Enrolled Customers and Load, by Industry Group – *DBP*

Industry Type	PG&E DBP Number of SAIDs	PG&E DBP Sum of Max MW	SCE DBP Number of SAIDs	SCE DBP Sum of Max MW
1. Agriculture, Mining & Construction	123	187.4	36	40.9
2. Manufacturing	305	535.0	375	793.7
3. Wholesale, Transport, other Utilities	178	176.4	204	124.0
4. Retail stores	78	19.3	172	86.0
5. Offices, Hotels, Health, Services	309	330.3	260	197.8
6. Schools	41	38.6	224	84.3
7. Entertainment, Other Services, Gov't	92	96.3	97	176.6
8. Other/Unknown	1	0.3	0	0.0
TOTAL	1,127	1,383.6	1,368	1,503.2

Figures 2.8 through 2.12 illustrate relationships between load factor, load variability and baseline accuracy for PG&E DBP and CBP, SCE DBP and CBP, and SDG&E CBP respectively, for the following five industry groupings, where one group combines three commercial-type groups in the standard list:

1) Agriculture, Mining and Construction;
2) Manufacturing;
3) Wholesale, Transportation and Other Utilities;
4) a combined grouping of industry groups 4 (Retail stores), 5 (Offices, Hotels, Finance, Services), and 7 (Entertainment, Other services and Government), and
6) Schools.

The figures are necessarily small in order to allow visual comparison of differences between industry types. Figures are not provided for industry groups with zero or very small numbers of customers (*e.g.*, Agriculture, Mining, and Construction; and Schools for SCE CBP and DBP and SDG&E CBP). The patterns of load variability and baseline accuracy relative to load factor differ substantially by industry grouping. In general, the load variability is *lower* and baseline accuracy *higher* for the combined commercial-type accounts (Industry groups 4, 5, and 7), with a much greater portion of values falling in bands below 0.2 or 0.3 (20 or 30 percent).

Results for Manufacturing (Industry 2) also show a majority of values in the low-variability and high baseline-accuracy area, although a number of values are larger than 0.2 or 0.3. The first and third industry groups generally show much greater variability across customer accounts than do the others, with a number of relatively high load-variability customers across a wide range of load factors. Finally, where present, many School customers have relatively low load factors and high load variability.

Figure 2.8. Relationship between Load Factor, Average CV and Baseline Accuracy – *PGE DBP – By Industry Group*

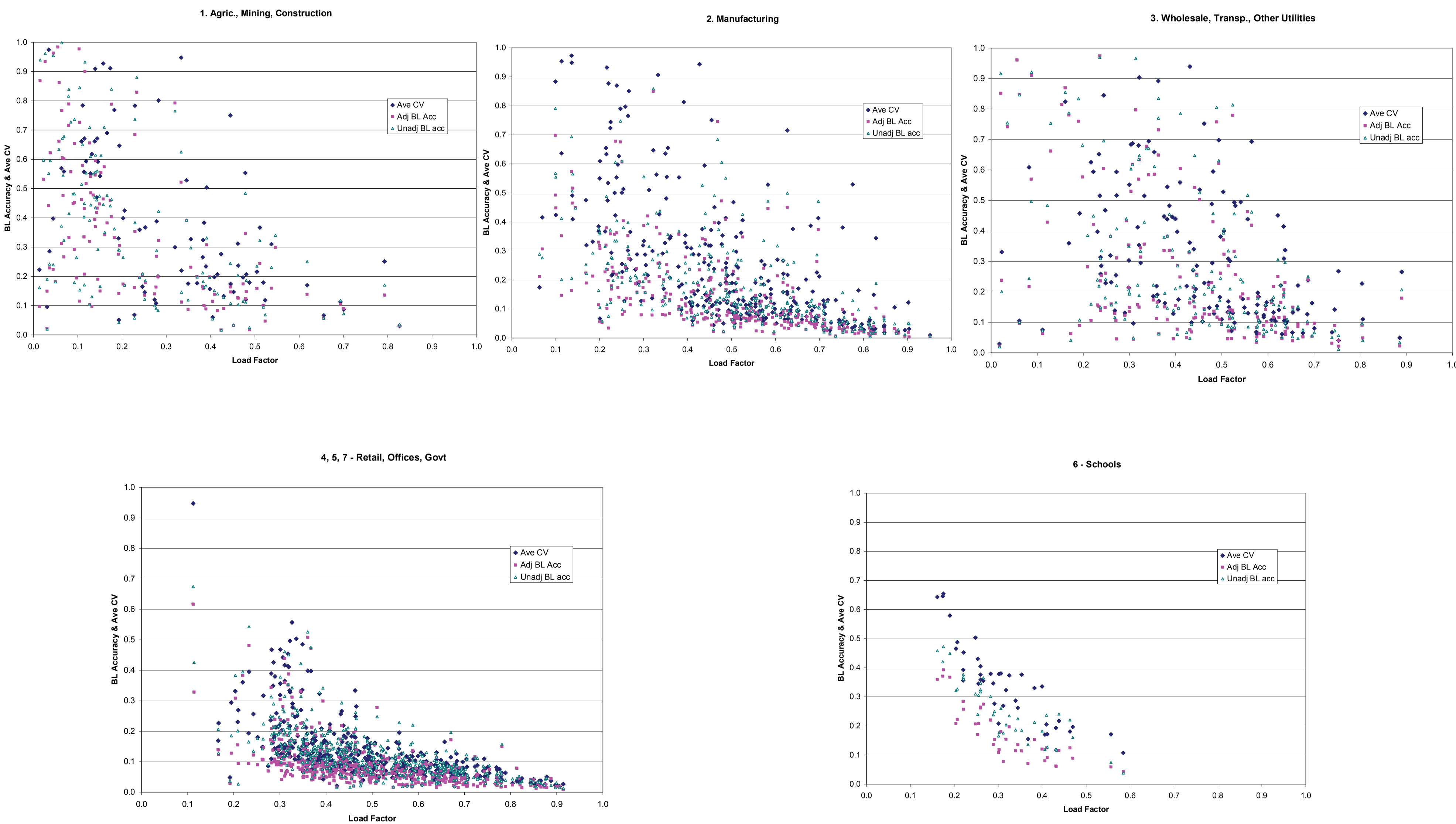


Figure 2.9. Relationship between Load Factor, Average CV and Baseline Accuracy – *PGE CBP – by Industry Group*

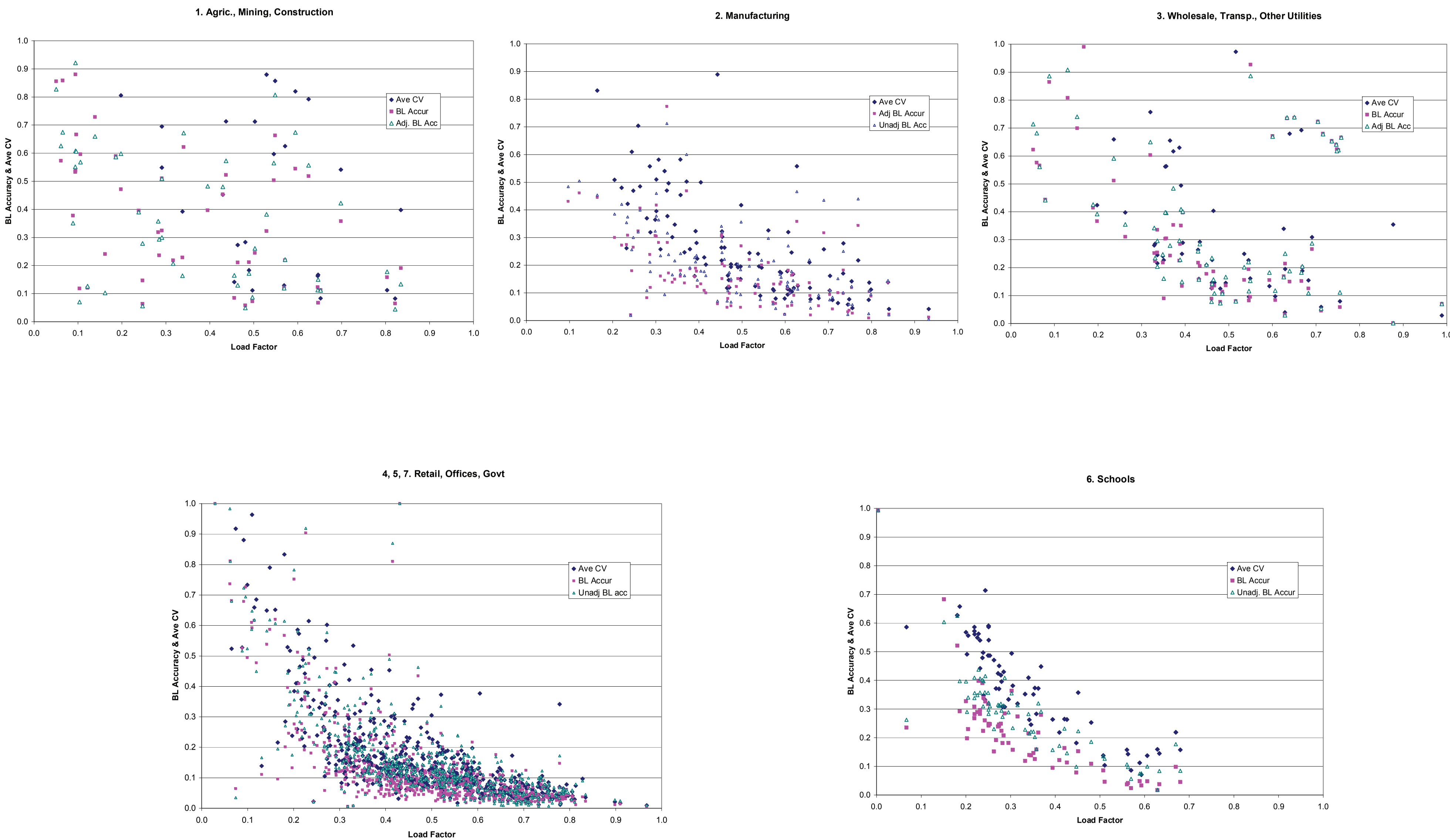
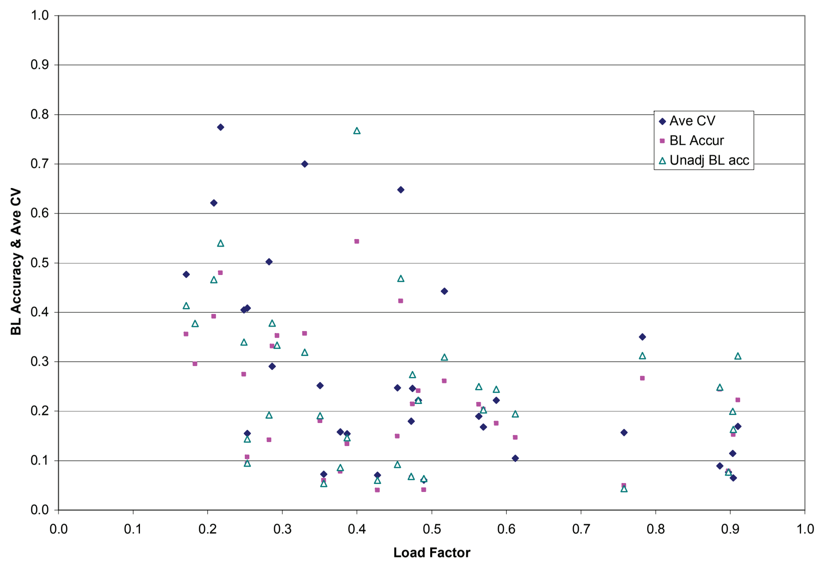
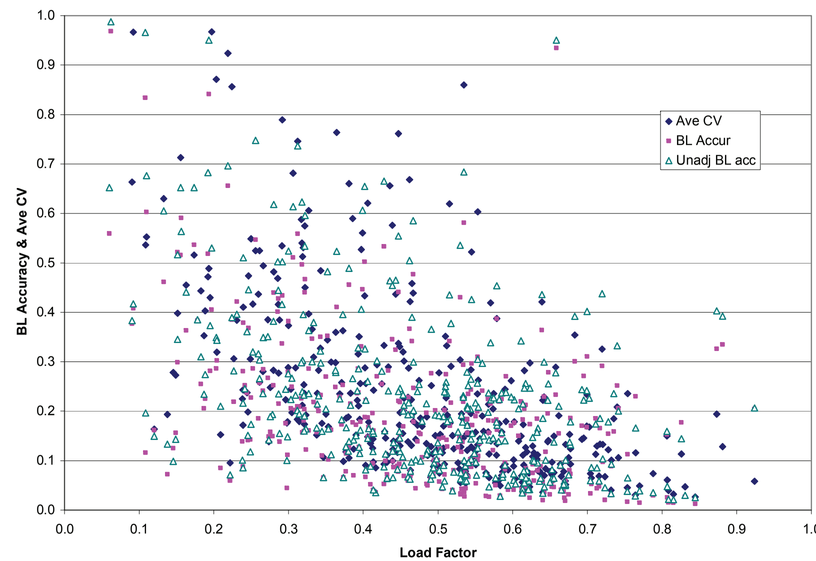


Figure 2.10. Relationship between Load Factor, Average CV and Baseline Accuracy – *SCE DBP – by Industry Group*

1. Agric., Mining, Construction



2. Manufacturing



4, 5, 7. Retail, Offices, Govt

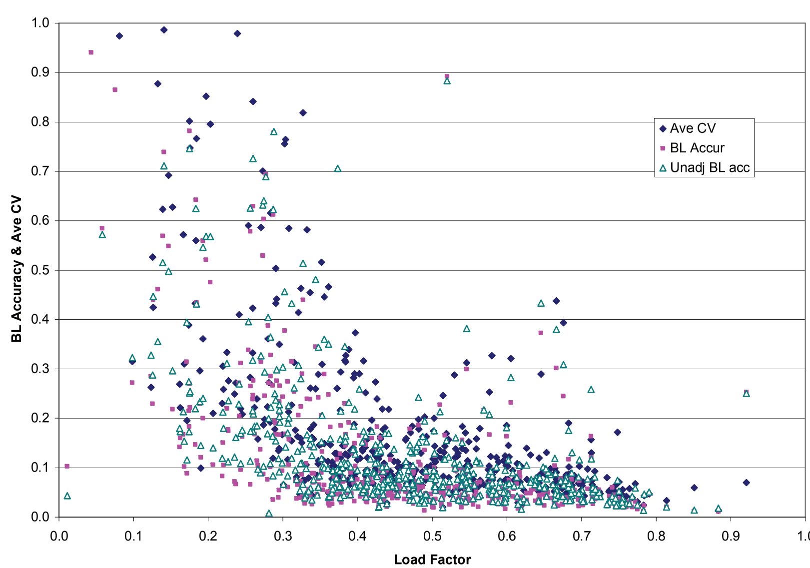
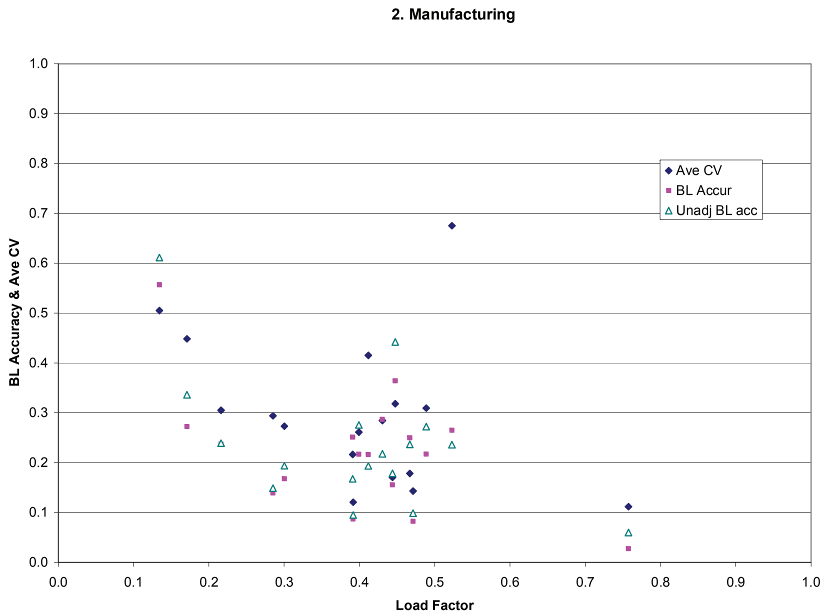
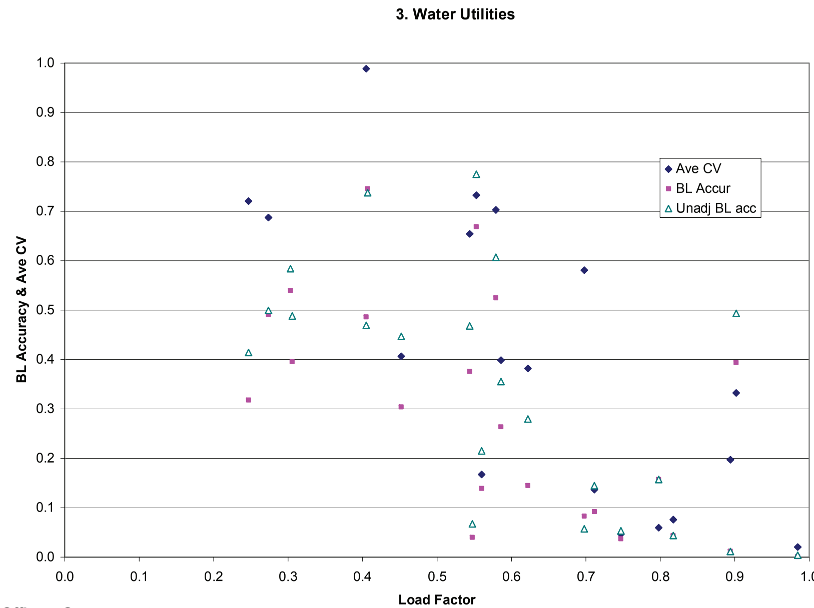


Figure 2.11. Relationship between Load Factor, Average CV and Baseline Accuracy – SCE CBP – by Industry Group





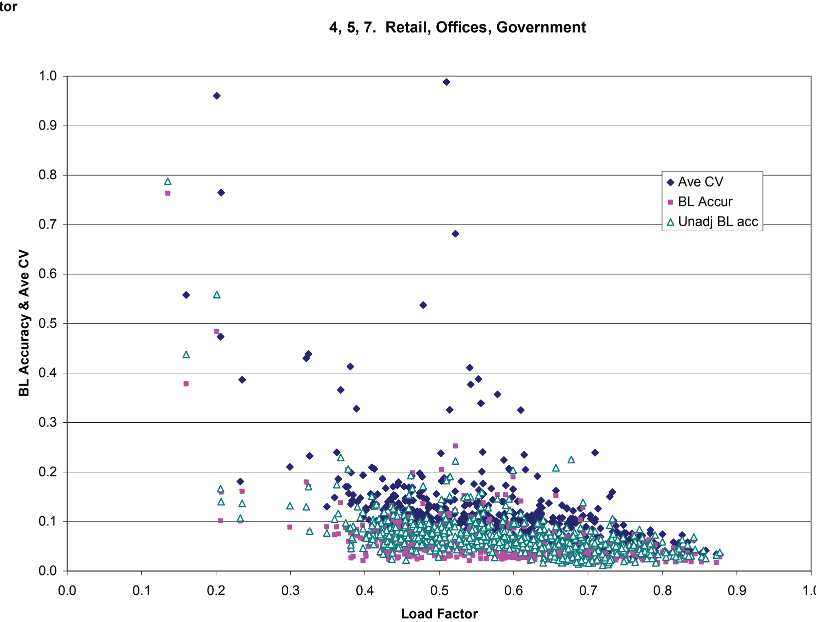
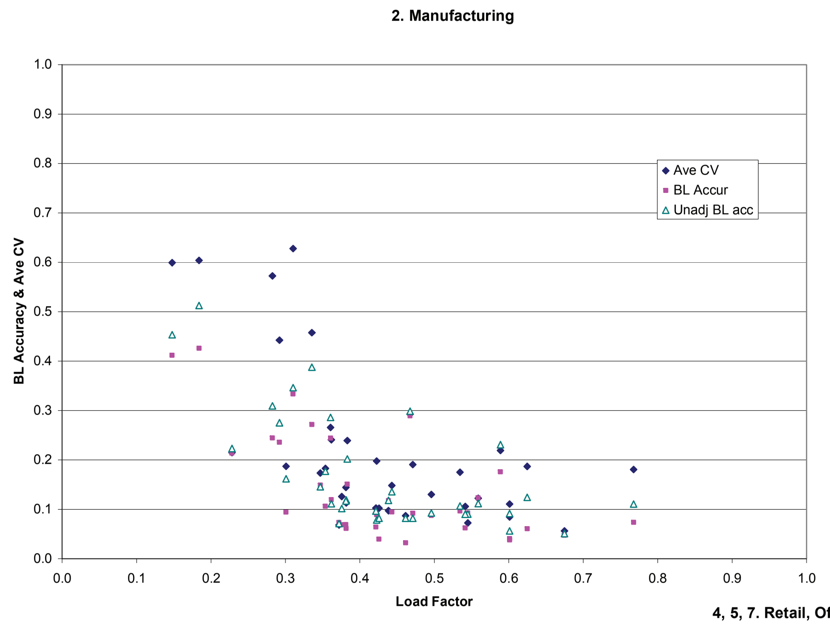
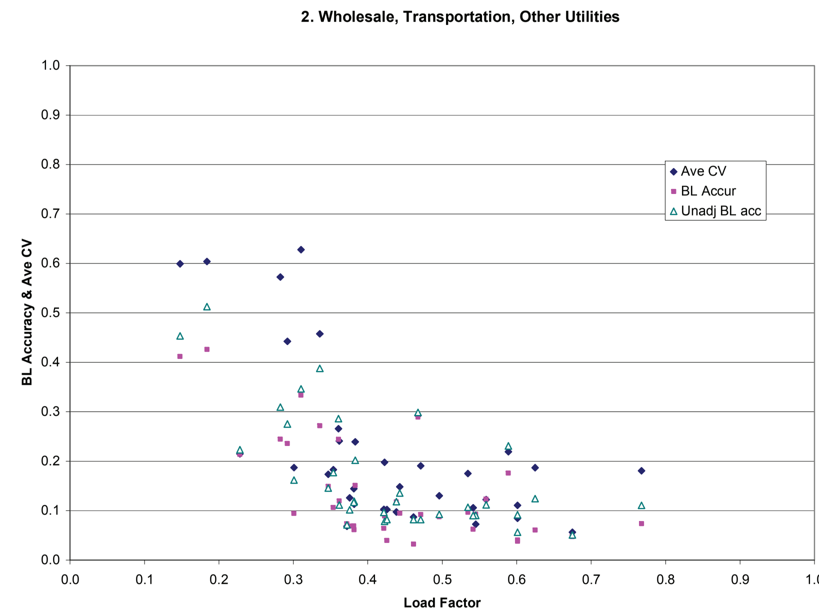
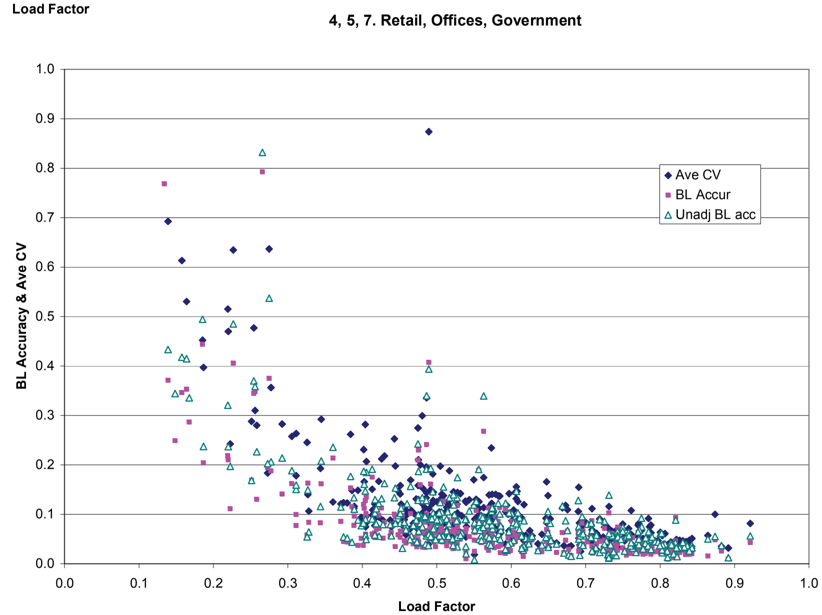


Figure 2.12. Relationship between Load Factor, Average CV and Baseline Accuracy – *SDG&E CBP – by Industry Group*







2.4 Load impacts, load variability and baseline accuracy

This sub-section expands on the previous analyses to provide information on the relationships between the customer-level load impacts that were estimated for program-year 2009, and measures of load variability and estimated baseline errors. The objective of this analysis is to explore the potential implications of different HVLC criteria on baseline accuracy and the program load impacts that might be foregone from these programs if certain customers were excluded by the choice of criterion.

The information is provided in the form of graphs. Two graphs are shown for each program. One shows values for customers for whom positive load impacts were estimated for program-year 2009 (including the estimated load impacts). The other shows values for customers for which estimated load impacts were either zero or negative (load increases). For clarity of the graphs, load impacts are shown only for the former groups of customers. The graphs plot the following variables:

- Average hourly estimated load impact for the typical event in 2009 (in cases where positive load impacts were estimated);
- Average CV of afternoon load;
- Mean or Median % error for Unadjusted 10-in-10 baseline[13];
- Mean or Median % error for Adjusted 10-in-10 baseline; and
- Load factor (Average kW/ Maximum kW, for the summer months).

In these graphs, the horizontal axis represents individual customer accounts (whereas in the graphs in the previous sub-section the horizontal axis represented values of load factor). Values for each of the above factors are shown relative to the vertical axes. Average hourly load impacts (where shown) are relative to the left axis, and all other variables against the right axis. The observations are sorted by values of the average CV; thus, customer load variability increases from left to right.

2.4.1 CBP

A significant amount of information is included on each chart, some of which are "cleaner" than others in terms of patterns of the reported values. For that reason, the first chart is described in more detail than the others in order to give the reader a benchmark for reviewing subsequent figures. Figure 2.13 shows results for those SDG&E's CBP customer accounts for which positive load impacts (*i.e.*, load reductions) were estimated in 2009. The symbols on the chart represent the following five factors for each of the 220+ customer accounts with positive load impacts:

[13] Average, or mean percentage baseline errors are shown in the CBP graphs due to the lack of unusually high values. In the case of DBP, a number of customers had very large *mean* percentage errors, due to at least a few cases of very large errors. Thus, *median* percent errors are shown in the DBP graphs. In both cases, percentage baseline errors reflect both *positive* (under-stated baseline) and *negative* (over-stated baseline) values. For convenience in illustration, the graphs in the previous sub-section showed RRMSE values, which may be thought of as the mean of the *absolute values* of the percentage errors, and are thus always positive. That is, RRMSE values show the magnitude but not the direction of baseline error.

- *Load variability*, measured by the Average CV (relative to right axis), is shown by the triangular symbols that form an increasing curve beginning near zero in the middle of the chart.
- *Load factor (LF)* is shown by the diamond-shaped symbols in the upper part of the chart, which generally form a decreasing pattern from left to right (*i.e.*, LF is generally higher when Average CV is low, and then falls as CV increases).
- Mean % errors for the *unadjusted* baseline are shown by the light * symbols that lie largely above (indicating *under-stated* baselines), but sometimes below the bold horizontal 0 line.
- Mean % errors for the *adjusted* baseline are shown by the darker diamond symbols, which generally lie below the unadjusted values.
- *Average hourly load impacts* per event (left axis) are shown by the height of the lines rising from the horizontal axis.

Nearly 190 of these 220+ customers have relatively low load variability, measured by average CV, of 20 percent or less, load factors ranging between about 40 and 90 percent, and mean % errors for adjusted baselines of less than 10 percent. The remaining customers show increasingly variable loads, lower load factors, and less accurate baselines. Among those customers are two with very large estimated load impacts. A review of the 2009 load-impact regression equations for those two customers indicates that despite the relatively high load variability, the estimated hourly load-impact coefficients for each event were estimated with considerable accuracy (*e.g.*, the average event-hour t-statistics were – 11.9 for one customer and – 3.6 for the other).

Figure 2.13. Load Variability, Baseline Errors and Load Impacts – *SDG&E CBP (Customers with Estimated Load Reductions)*

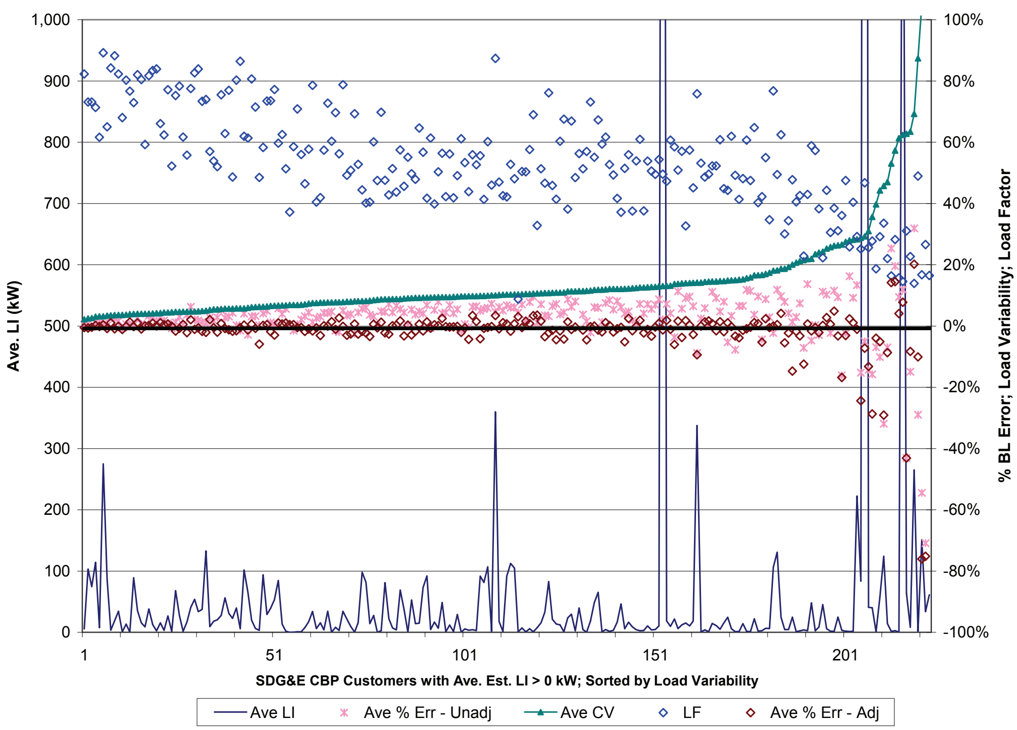
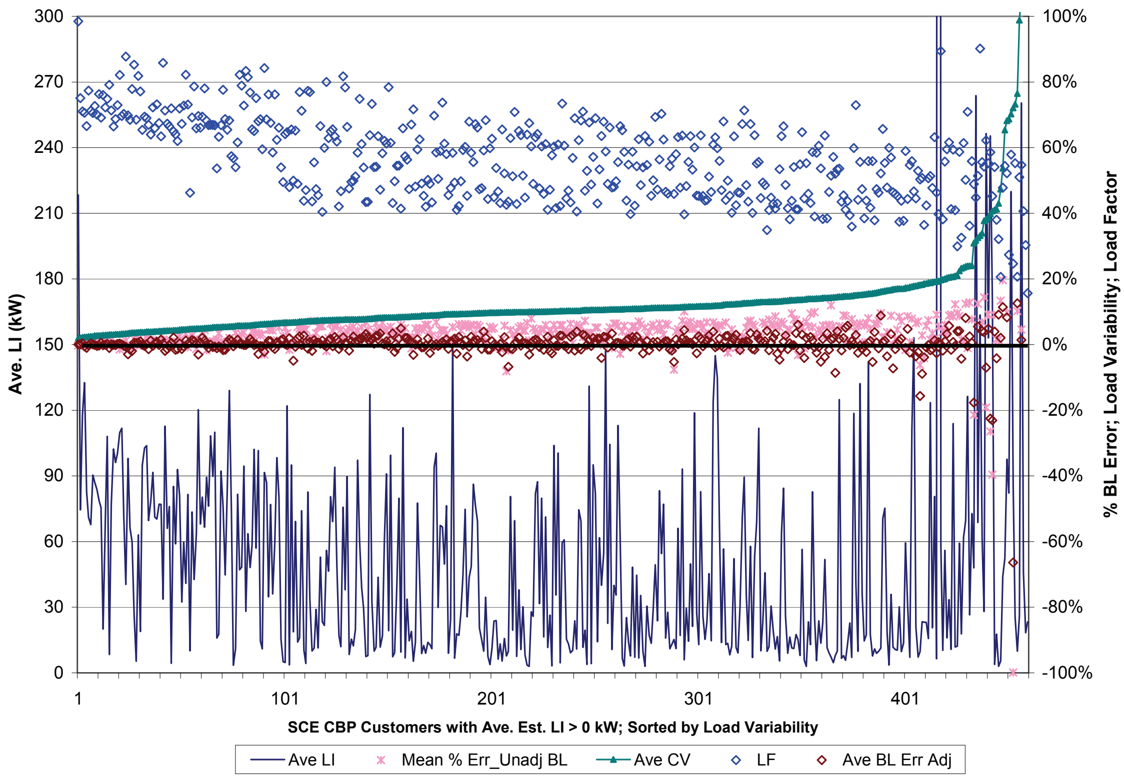


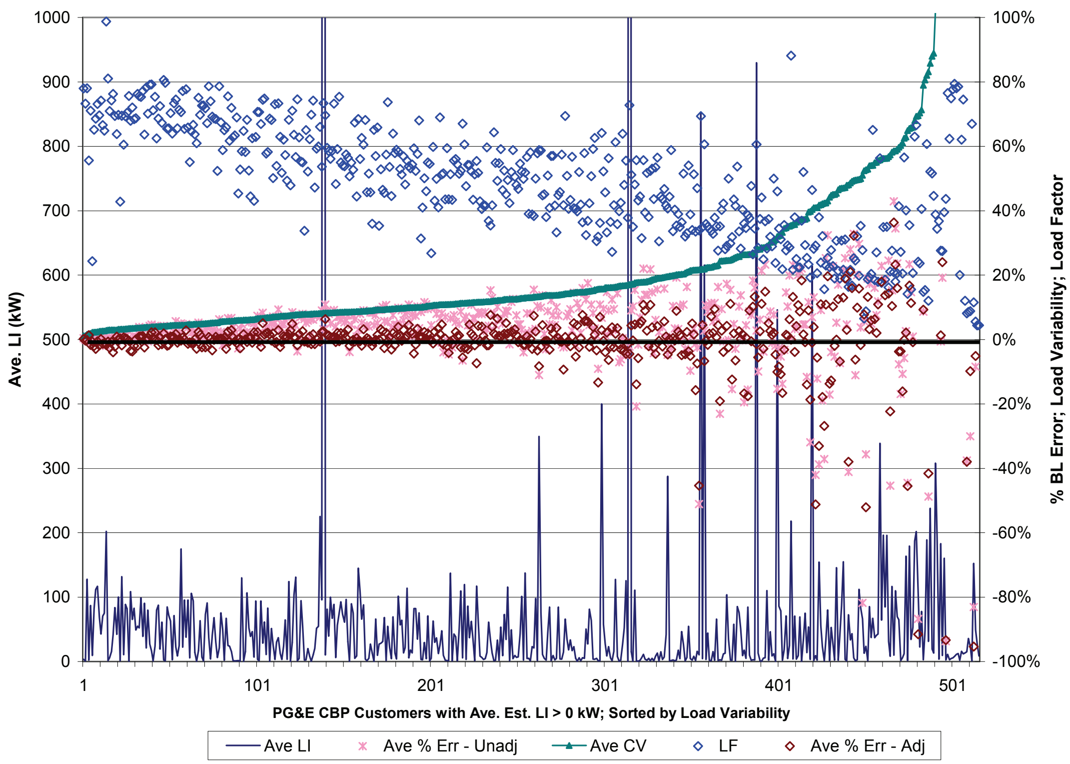
Figure 2.14 shows comparable results for SCE CBP. In this case, 420 out of 460 customers accounts for which positive load impacts were estimated in 2009 had average CV values less than 0.20 and average baseline errors of less than about 10 percent. The average CV values for the customers at the far right rise dramatically, which is an indication of their high variability, along with their estimated baseline errors.

Figure 2.14. Load Variability, Baseline Errors and Load Impacts – *SCE CBP*



For PG&E's CBP, shown in Figure 2.15, a somewhat smaller share of customer accounts (about 340 out of 516) had average CV values below 0.20 and relatively low average baseline errors.

Figure2.15. Load Variability, Baseline Errors and Load Impacts – *PG&E CBP*



Figures 2.16 through 2.18 provide similar information for CBP customers for whom zero or negative load impacts (load increases) were estimated in 2009.

Figure 2.16. Load Variability, Baseline Errors and Load Factor – *SDG&E CBP*
(Customers with Estimated Zero & Negative Load Impacts)

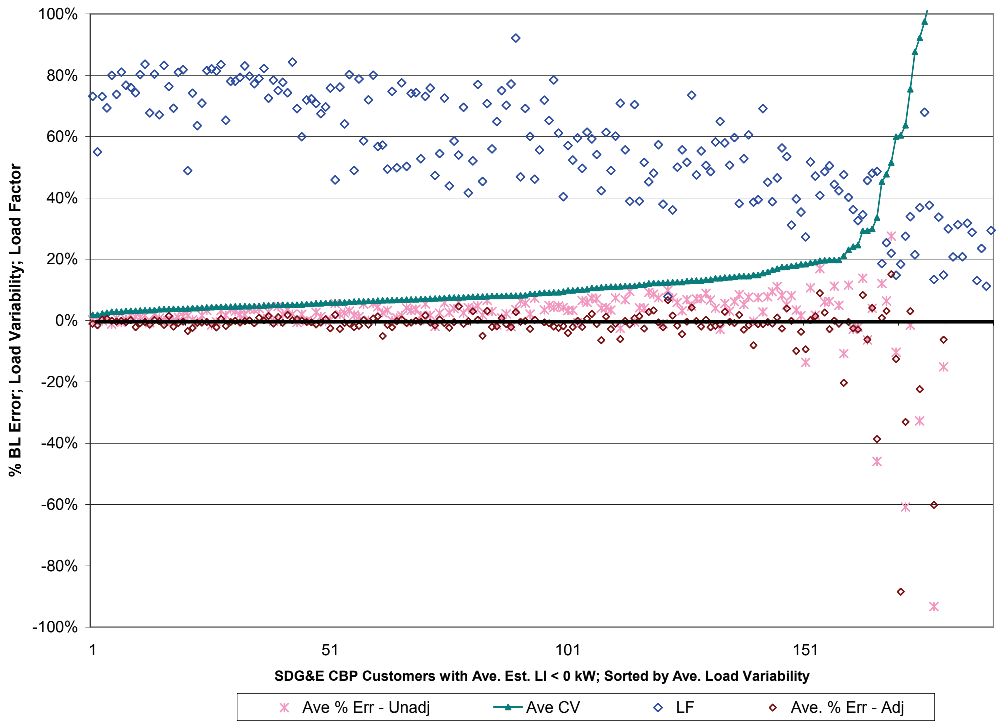


Figure 2.17. Load Variability, Baseline Errors and Load Factor – *SCE CBP*
(Customers with Estimated Zero & Negative Load Impacts)

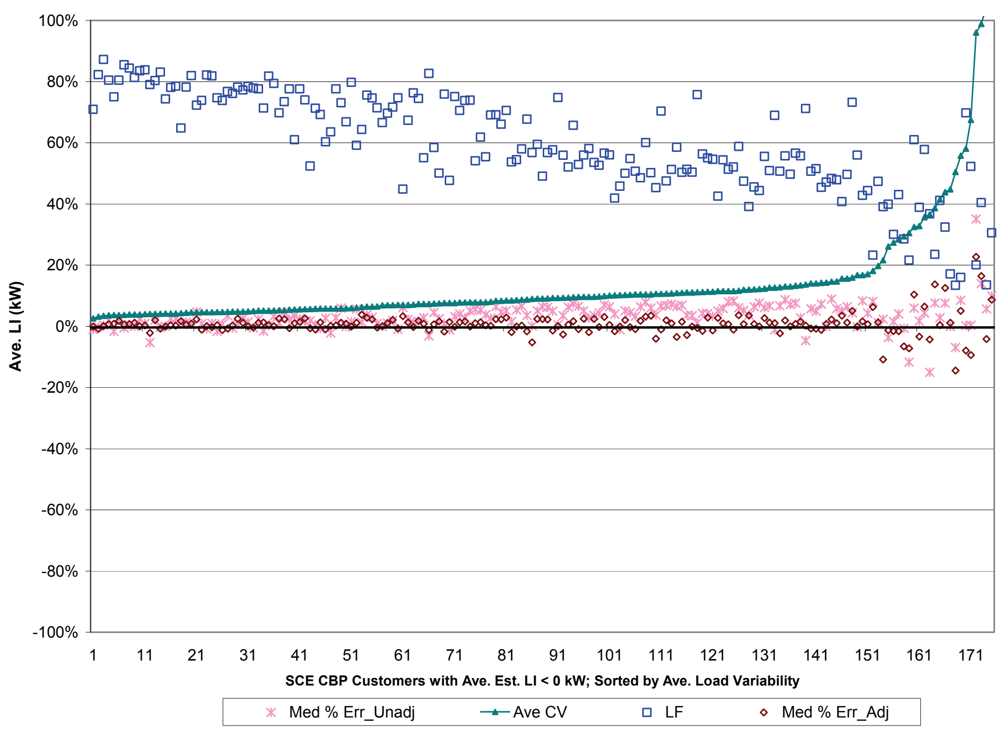
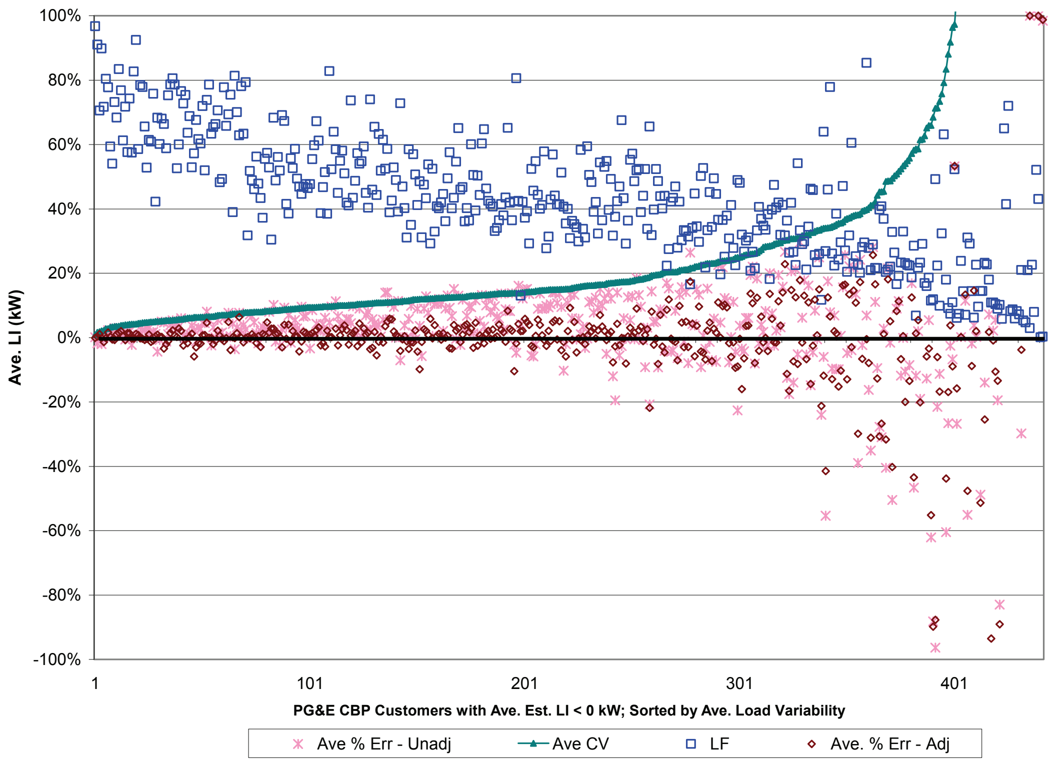


Figure 2.18. Load Variability, Baseline Errors and Load Factor – *PG&E CBP (Customers with Estimated Zero & Negative Load Impacts)*



2.4.2 DBP

The results for the two DBP programs produce results that differ substantially from those for CBP. Figure 2.19 shows results for SCE's DBP customers for whom we estimated positive load impacts greater than 10 kW in 2009, while Figure 2.20 shows values for customers for whom zero or negative load impacts were estimated.[14] In Figure 2.19, less than half of the customer accounts have average CV values of less than 0.20, and many of the remaining accounts have load factors of less than 40 percent and large estimated baseline errors.[15]

As with SDG&E CBP, we explored the potential effect of load variability on estimated load impacts by examining the 2009 load impact regression results for seven customer accounts that had large estimated load impacts (*e.g.*, greater than 1 MW) and relatively high load variability (*e.g.*, greater than 0.2). Of those seven, all but one submitted bids for the majority of DBP events. Interestingly, even with average CV's ranging from 0.2 to 0.3, and estimated baseline relative error of 20 to 30%, our regression equations estimated statistically significant load reductions for half to 90 percent of the events for five of the seven customers. That is, even with substantial load variability, the regressions were able to estimate significant load impacts. Without further analysis, it is

[14] Most all of SCE's DBP customers appeared to submit standing bids for every event, even though they may have had no intention of responding, and in fact may have increased usage on DBP event days.
[15] The percent baseline errors for a number of customers were extremely large for some simulated-events, so we report *median* % errors in this case.

not known how these estimates compare to those that were calculated using the program baseline.

Finally, for the other two customers, significant load reductions were estimated for only 30 to 40 percent of the event hours. Notably, these two customers had two of the three highest average CV values, thus demonstrating considerable load variability. For those customers, the patterns of non-significant coefficients suggest that they may have been attempting to reduce load (*e.g.*, many coefficients were negative, but were less than half the magnitude of those for events for which significant coefficients were estimated), but the extensive load variability did not permit clear estimation of load impacts.

Figure 2.20 shows results for SCE's DBP customers for whom zero or negative load impacts were estimated. The patterns of load variability and baseline errors are generally quite similar to those in the previous figure for customers with positive load impacts.

Figure 2.19. Load Variability, Baseline Errors and Load Impacts –
SCE DBP (Positive Load Impacts)

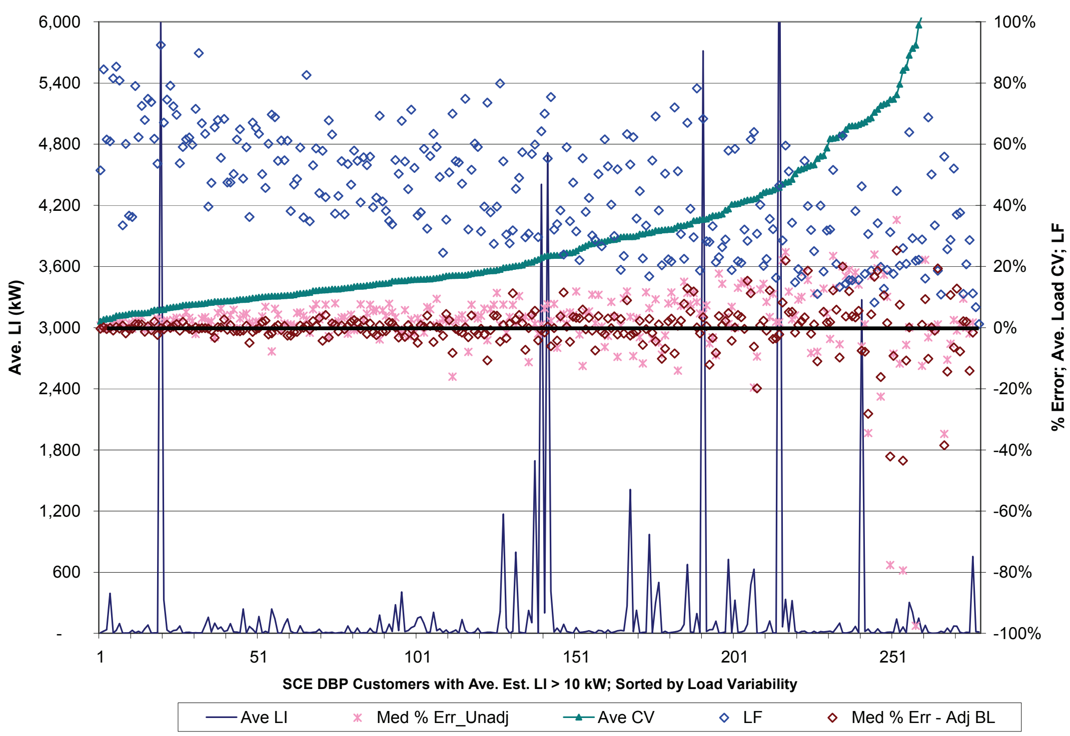


Figure 2.20 Load Variability, Baseline Errors and Load Impacts –
SCE DBP (Zero or Negative Load Impacts)

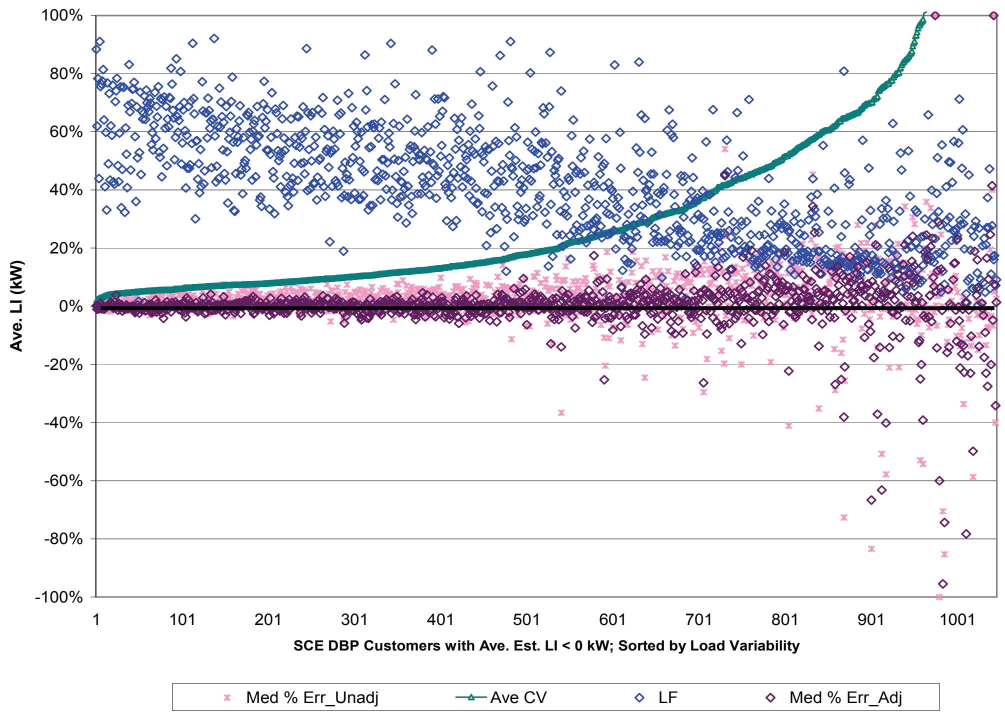


Figure 2.21 and 2.22 show results for PG&E DBP bidders and non-bidders. Note that PG&E called only one test event, which was also a BIP event day, for which less than 100 customer accounts submitted bids. Several customers produced extremely large load impacts to meet BIP requirements.[16] All of the DBP bidders for this test event had low load variability, high load factors, and small baseline errors (for the simulated-events). The non-bidders in Figure 2.22 demonstrate similar load variability and median baseline errors to those of the SCE DBP customers that had small or negative load impacts (Figure 2.20).

[16] In the DBP load impact evaluation, we did not attribute those large load impacts to DBP during the hours of the BIP event. However, many of the customers maintained their large load reductions into the subsequent DBP event hours after the BIP event ended.

Figure 2.21. Load Variability, Baseline Errors and Load Impacts – *PG&E DBP Bidders*

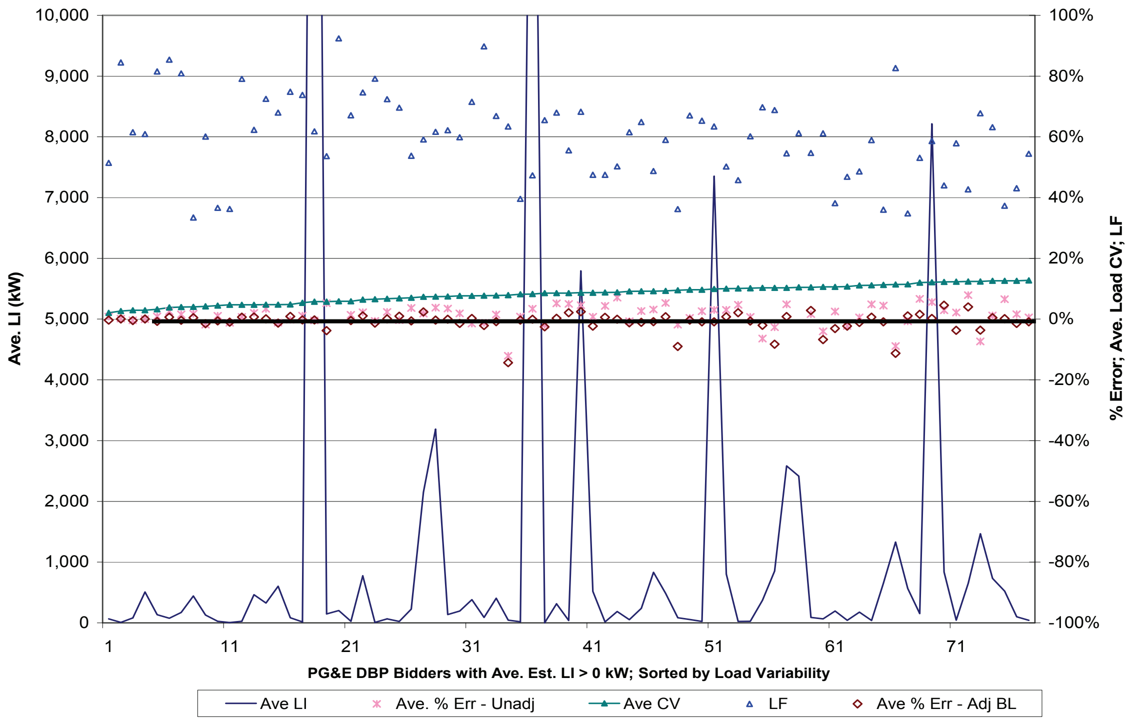
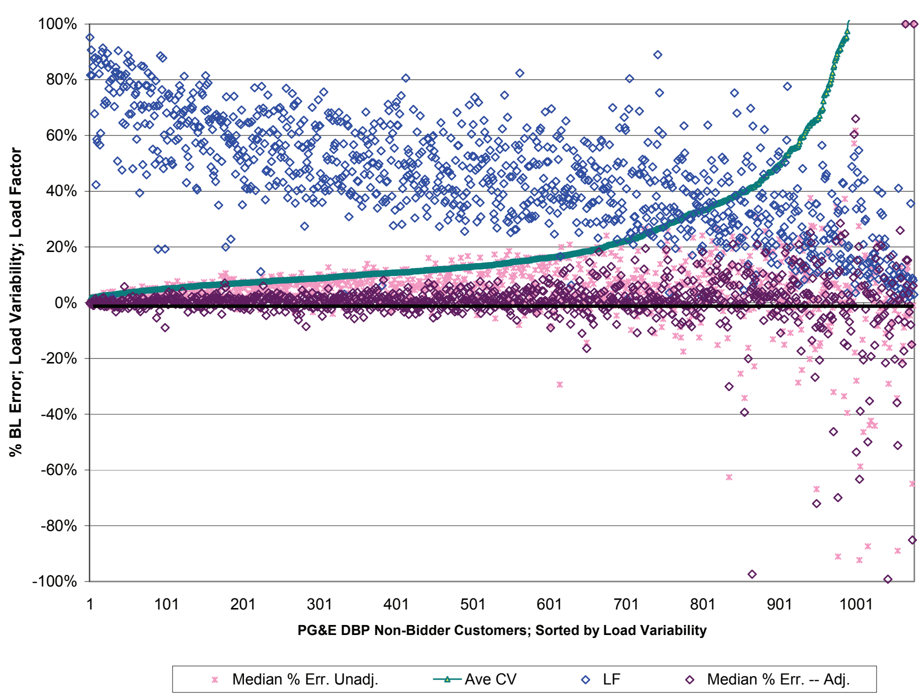


Figure 2.22. Load Variability, Baseline Errors and Load Factor – *PG&E DBP Non-Bidders*



2.5 Conclusions

The various figures shown in this section suggest a number of conclusions regarding the load variability of these CBP and DBP customer accounts, including the following:

- There is a direct relationship between a detailed measure of inherent *load variability* such as the average CV of afternoon loads and estimates of *baseline accuracy* (for both unadjusted and adjusted baselines).
- More easily obtained measures of load variability, such as load factor, are directly related to the more detailed average CV measure, however the relationship is not extremely tight. For example, customers with relatively low load factors of around 40 percent are *likely* to have a relatively high average CV, but some can have CVs of less than 20%.
- Customer accounts in both programs at all the utilities show distributions of load variability characterized by relatively large percentages of customers with relatively low load variability (*e.g.*, average CV less than 20%, indicating that the customers' standard deviation of afternoon load is 20% of the mean, or average, value), although the distributions vary by program.
- Distributions of load variability for CBP customer accounts generally exhibit smaller percentages of customers with relatively high load variability (*e.g.*, 10 to 20 percent of customers have an average CV greater than 20 to 30%) than do DBP customer accounts, for which as many as 30 to 50 percent of customers may exceed that degree of load variability.
- Distributions of load variability also differ substantially by industry type. *Commercial-type* customers (*e.g.*, retail stores, offices, government buildings) generally display the lowest percentages of highly variable loads. The *first and third industry groups* (*i.e.*, agriculture, mining and construction; and wholesale, transportation and other utilities) show the greatest degrees of load variability. *Manufacturing* customers generally include a majority that display relatively low load variability, but also a substantial portion with high load variability. Finally, where present, a large portion of *School* customers have relatively low load factors and high load variability.

The next section investigates the relationship between load variability and customers' DR program credits, and recommends an HVLC criterion.

3. RECOMMENDED HVLC CRITERION AND SCREENING TOOL

This section 1) begins with an analysis of the potential effect of load variability on potential errors in DR payments due to resulting baseline inaccuracies, where the focus is primarily on potential customer effects, 2) provides our recommended HVLC criterion, 3) provides statistics on the number of customers, amount of load, and percentage of the estimated 2009 program load impacts that are accounted for by HVLC customers under this criterion, and 4) describes an HVLC screening tool that can be used with readily available billing information on customers' industry group, size and load factor to predict the likelihood of exceeding the HVLC criterion.

3.1 Potential Effects of HVLC Criterion on DR Payment Errors

As noted earlier, customers' load variability affects the accuracy of baselines used to calculate program load impacts, and therefore the financial payments that are made to customers for their load response. In this sub-section, we describe a simulation designed to illustrate the potential effects of load variability on payments to customers for bid or nominated load reductions. We note that the effect of load variability and baseline errors on program credit payments is not completely direct, due to various performance restrictions, particularly for CBP. For example, a baseline error that implies a 100 percent over-stated load impact does not necessarily imply a 100 percent DR credit overpayment, because of restrictions on payments for load reductions in excess of bid amounts.

3.1.1 Design of simulated DR payments

To examine the potential financial effects on customers of being an HVLC we simulated DR credit payment errors for each of the enrolled CBP and DBP customers that were analyzed in Section 2, under an assumption that each customer performs (*i.e.*, reduces load) in the exact amount of their simulated bid or nomination amount. We then use information on each customer's adjusted 10-in-10 baselines (with the 20 percent adjustment cap) for the simulated events described previously to estimate the extent to which DR credit payments are likely to differ from those that would be made if the consumers' baseline loads were estimated without error.

Because we wish to examine *simulated* (rather than actual) event days (so that we know customers' true baseline load, which is their *observed* load on the simulated event day), and to simplify the analysis, we need to make an assumption regarding the amount of load that each customer intends to reduce. For simplicity, we assume that all customers reduce load by 10 percent of their observed load in each event hour of the simulated event days, and that the load reduction exactly matches their bid (for DBP) or nomination (for CBP) amount. We then calculate simulated DR credit payments based on load reductions implied by the adjusted 10-in-10 baseline (where values of baseline errors, along with load variability, were illustrated in the graphs in Section 2), and compare those to the payments that would be made based on the known, or observed baseline.

For DBP, it is a relatively straightforward exercise to simulate DR credit payments and the errors associated with errors in the estimated baseline load. Specifically, we assume that each customer has selected the adjusted 10-in-10 baseline method. We then compare our calculated baseline loads for the simulated events to the simulated event-hour usage, which is the observed load in each event hour reduced by the assumed 10 percent load response. We then calculate two payments:

1) the payment that the customer would have received if the baseline had matched the customers "true" baseline (*i.e.*, its actual usage during the simulated event hours), so that the customer gets paid the DBP credit for all of its 10 percent load reduction); and
2) the payment that the customer would have received under the adjusted 10-in-10 baseline, imposing the program-specific restrictions (*e.g.*, SCE pays a pro-rated credit for load reductions between 50 percent and 200 percent of the bid amount).

For comparison purposes, we calculate *percentage payment errors*, calculated as (10-in-10 Adjusted Credit – True Credit) / True Credit. Therefore, negative percentage payment errors mean the customer was underpaid using the 10-in-10 adjusted baseline, and positive values mean the customer was overpaid.

For CBP, the program credit calculations are more complicated because customers receive both capacity credits and energy credits. For simplicity, and because our understanding is that the capacity credits provide the bulk of the credit payments, we focus on errors in the capacity credits. For each event hour, we calculate the *hourly delivered capacity ratio*, the factor that is used to determine the percentage of the capacity credit that is paid. Under CBP rules, customers are paid no more than 100 percent of their nominated load reduction (which we again assume is 10 percent of the observed load). For performance between 90 and 100 percent of the nominated reduction, the credit is pro-rated; for performance between 75 and 90 percent of the nominated level, the credit is reduced to 50 percent; for performance between 50 and 75 percent, no credit is paid; and for performance below 50 percent of the nominated level, a penalty is assessed. We perform these calculations using both the "true" baseline (actual load) and the 10-in-10 adjusted baseline. The percentage difference between the credits is the metric we use to compare across customers. Note that overpayments (*i.e.*, positive percentage payment errors) are not possible for CBP customers in this exercise, since customers do not receive capacity payments for more than their nominated capacity, and we assume that the nominated capacity is equal to the load impact provided by the customer.

The focus of these calculations is to identify customers who are likely to be underpaid for actions that they actually took (*i.e.*, our assumption is that the customers actually achieve their 10 percent load reduction relative to their true baseline). We could have performed a similar calculation that attempted to identify customers who, due to baseline errors, would receive credits without providing load impacts. However, we believe that it is more appropriate to consider the HVLC definition in terms of preventing customers from signing up for a program that will not properly compensate them for load response that they actually provide.

3.1.2 Simulation results

The results from the credit payment simulations are quite different for DBP and CBP. Table 3.1 shows the *average* percentage credit payment errors for HVLC and non-HVLC customers enrolled in *DBP*, based on a range of potential HVLC criteria based on average CV of load. The first row of results corresponds to the case of setting the HVLC criterion equal to an average CV value of 0, thus defining *all* customers as HVLC. In this case, the average credit payment error is -24 percent (indicating that the DBP customers as a whole are *underpaid* by 24 percent, on average). As the threshold is made less restrictive, the average percentage payment error increases for both the HVLC and non-

HVLC customers.[17] The far-right column indicates the share of customers that is classified as HVLC relative to the threshold shown in the leftmost column.

As illustrated in Table 3.1, for DBP customers, there are substantial differences in average payment errors between the HVLC and non-HVLC groups. For example, at a CV = 0.30 threshold, HVLCs account for 35 percent of enrollees and have an average payment error of -40 percent, while non-HVLCs have an average payment error of -16 percent, or less than half that for HVLCs.

Table 3.1. Average Credit Payment Errors for Various HVLC Definitions, *DBP*

CV-Based HVLC Threshold	HVLC Credit Error	Non- HVLC Credit Error	HVLC Share of Customers
0.00	-24%	.	100%
0.05	-26%	-2%	93%
0.10	-30%	-9%	72%
0.15	-35%	-12%	55%
0.20	-37%	-14%	45%
0.25	-39%	-15%	39%
0.30	-40%	-16%	35%
0.35	-42%	-17%	31%
0.40	-44%	-17%	27%
0.45	-44%	-18%	24%
0.50	-45%	-19%	22%
0.75	-46%	-21%	12%
1.00	-50%	-22%	8%

The story is somewhat different for *CBP* customers, as shown in Table 3.2. For this group, the difference in average payment errors between the HVLC and non-HVLC groups is much smaller. This is due to the fact that we focused on errors in capacity credits, which are reduced by 50 percent when load reductions fail to reach 90 percent of their nominated levels. The steep decline in credit payments causes a high proportion of CBP customers to incur a significant reduction in credit payments relative to the payments that would be expected without baseline error, due to errors in estimating baseline loads.[18] Note that our method may overstate the extent of these credit payment reductions, as we do not allow for the diversity benefits of aggregated loads. (That is, we examine each service account separately, and not as part of their aggregated load.)

[17] This is possible because the numbers of customers in each group change as the threshold changes. The overall average across all customers remains the same regardless of the HVLC threshold (the weighted average of the values in the HVLC and non-HVLC column always equals – 24 percent).
[18] The relatively large average payment errors are caused by averaging across values that in numerous cases indicate negative errors of 50 percent or more due to the steep drop in capacity credit payments whenever the estimated load reduction is less than 75 to 90 percent of the nominated load, which can occur with relatively small baseline errors.

Table 3.2 Average Credit Payment Error for Various HVLC Definitions, *CBP*

CV-Based HVLC Threshold	HVLC Credit Error	Non- HVLC Credit Error	HVLC Share of Customers
0.00	-51%	.	100%
0.05	-54%	-35%	88%
0.10	-57%	-43%	60%
0.15	-61%	-46%	34%
0.20	-64%	-47%	25%
0.25	-66%	-48%	20%
0.30	-66%	-48%	17%
0.35	-67%	-49%	14%
0.40	-68%	-49%	12%
0.45	-68%	-49%	11%
0.50	-68%	-50%	9%
0.75	-70%	-50%	5%
1.00	-70%	-51%	4%

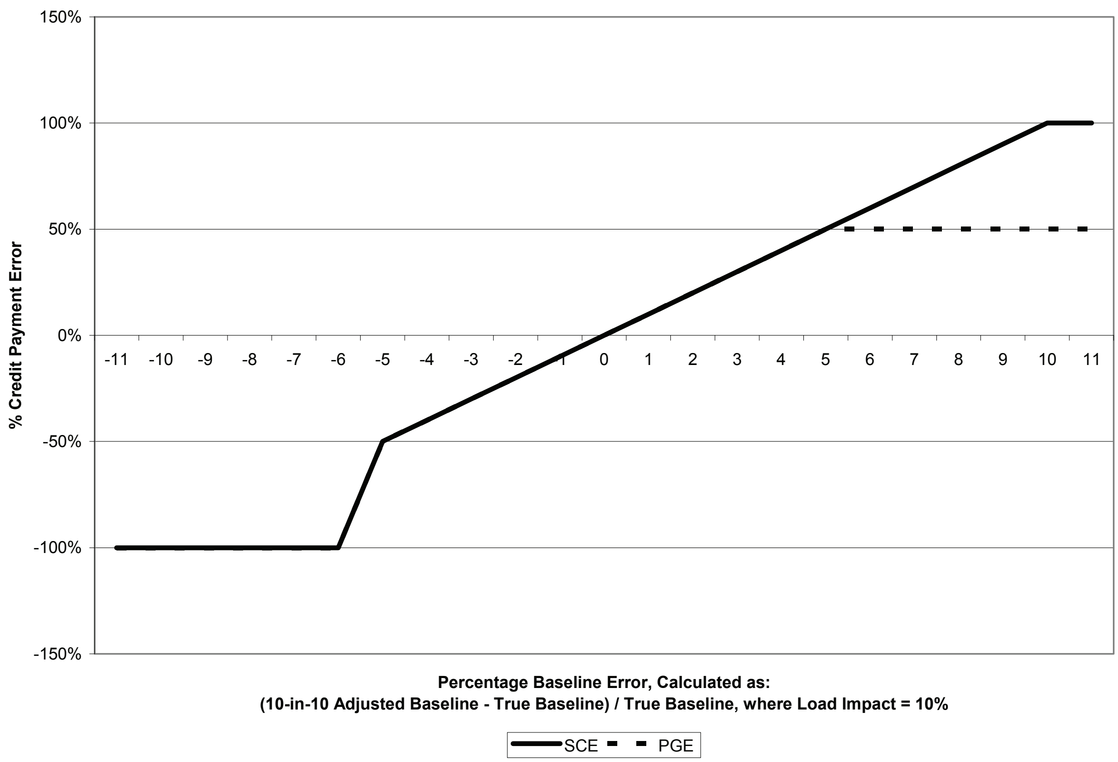
Note that all of the average credit errors in Tables 3.1 and 3.2 are negative, indicating that on average, customers are underpaid by the 10-in-10 adjusted baseline in this exercise. This result should be interpreted with some caution. As described above, negative payment errors ("underpayments") are expected for the CBP customers (*i.e.*, our assumptions don't allow for overpayments). For DBP, the underpayments (on average) are an artifact of the DBP tariff restrictions on the credit payment. That is, in each event hour, the customer's load impact must be at least half of its bid amount to be paid a credit, and the customer gets paid for load impacts up to 1.5 (PG&E) or 2 (SCE) times its bid amount.[19]

Figure 3.1 shows the relationship between credit payment errors and baseline measurement errors, where the baseline is calculated using the 10-in-10 adjusted method. Separate lines are shown for SCE and PG&E, as their programs have different maximum allowed payment levels. The values in the figure are calculated under the assumption that the customer reduces load by 10 percent relative to its true baseline. Notice that when the 10-in-10 adjusted baseline understates the true baseline (*i.e.*, negative percentage baseline errors), the credit payment error is *-100 percent* at only a -5 percent baseline error. Alternative, when the 10-in-10 adjusted baseline overstates the true baseline (*i.e.*, positive percentage baseline errors), a +5 percent baseline error only produces a *+50 percent* overpayment. This asymmetry of credit payment errors versus baseline measurement errors (in which a 5 percent baseline understatement produces a 100 percent underpayment, but a 5 percent baseline overstatement produces only a 50 percent overpayment) drives the overall negative average percentage credit payment errors that we observe in Table 3.1. That is, even if the 10-in-10 adjusted baseline is an

[19] In response to a question from one of the reviewers, we examined the effect of removing the 20 percent cap on baseline adjustments on the average payment errors in Tables 3.1 and 3.2. In general, the uncapped adjusted baseline leads to lower average payment errors, because the adjusted baseline is closer to the true baseline. As might be expected, the average percent error for CBP falls only modestly (- 48 percent versus -51 percent across all utilities at the 30 percent HVLC criterion). For DBP, the difference is larger (- 16 percent compared to - 24 percent overall at the 30 percent HVLC criterion).

unbiased estimate of the true baseline, we expect to observe negative percentage payment errors on average.[20]

Figure 3.1. Percentage DBP Credit Payment Errors versus Percentage Baseline Errors, Assuming a 10% Load Reduction



It is also important to note that our simulations do not include cases in which customers are paid for load impacts they did not provide (which are overpayments by definition). That is, our simulation assumed that all customers provided load impacts equal to 10 percent of their true baseline load.

3.2 Determine HVLC Criterion

In principle, a criterion for defining HVLC should satisfy certain properties. First, since high load variability is not an absolute characteristic, an HVLC criterion necessarily indicates a relative measure of load variability. Second, since high load variability implicitly suggests a somewhat exclusive property, an HVLC criterion should classify a relatively small percentage (certainly less than half) of customers as having that property. Third, since the stakeholders' interest in high load variability ultimately concerns its potential effect on baseline accuracy and DR financial payments, the HVLC criterion should be driven by evidence of those effects.

[20] Note that Table 3.1 shows the average of customer-specific percentage errors. The percentage error associated with the *total* credit payments across all customers is significantly smaller (-11 percent based on total credit payments vs. -24 percent for the average of the customer-specific percentage payment errors).

The relationships between load variability, baseline accuracy, and estimated load impacts were reported in Section 2 for the utilities' CBP and DBP customers, and the potential effects of high load variability on DR credit payment errors were examined in the previous sub-section. A review of the graphs in Section 2 and the credit payment errors in this section suggests that an HVLC criterion of an average coefficient of variation (CV) of afternoon load in the range of 0.20 to 0.30, or 20 to 30 percent could be supported. That is, the bulk of customers in at least some industry groups have average CV values below those levels, while a good share of customers with average CV values above those levels have values that are substantially greater. Finally, the analysis of potential DR payment errors suggests both that average payment errors for both CBP and DBP are relatively stable in the above range of average CV values, and that the payment restrictions for both programs limit the magnitude of potential payment errors due to extreme load variability.

Selecting a particular HVLC criterion involves a classic situation of attempting to compromise on the possibility of "Type I" and "Type II" errors. That is, a criterion that is overly restrictive risks identifying some customers as HVLC when their load patterns would actually support reasonably accurate baselines and DR payments. At the same time, a criterion that is overly lax risks not identifying some customers as HVLC when they could face potential undesirable payment errors. We take the somewhat conservative approach and conclude that a reasonable criterion for classifying DR program customers is an average CV value of greater than or equal to 0.3, or 30 percent.

Using this criterion, we can use summarize the characteristics of customer accounts identified as HVLC on the basis of the average CV values calculated earlier. These are reported in Section 3.3. Defining the HVLC criterion on the basis of the average CV metric does not imply, however, that the utilities necessarily need to calculate CV values for all of their potential DR program customers. As described in Section 3.4 below, we can estimate the likelihood that a given customer should be considered HVLC using a spreadsheet tool that uses only readily available information on industry type, size and load factor. We describe the likely accuracy associated with that estimation of HVLC.

3.3 Characteristics of Customers Meeting HVLC Criterion

Based on an HVLC criterion of an average CV of at least 30 percent, we may calculate various characteristics of the HVLC and non-HVLC customer accounts. These are shown in Tables 3.3 and 3.4.

3.3.1 Program-level HVLC and non-HVLC characteristics

Table 3.3 shows the number of customer accounts, average size, and average hourly load impacts for the average, or typical event, that were estimated in the 2009 load impact evaluations for the utilities' DR programs listed. Using the HVLC criterion recommended of an average CV of 0.3 or greater, the numbers of enrolled customers that are identified as HVLC average 25 percent of the total, though results differ substantially by utility and program. The percentages of HVLC customers are generally lower for CBP than for DBP. Average maximum demand (customer size) is roughly comparable between the HLVC and non-HVLC groups, with the exception of SCE CBP and SDG&E

CBP.[21] Overall, the HVLC customer accounts account for 25 percent of the total estimated average hourly load impacts for CBP and DBP in 2009. Again, results differ substantially across programs, with HVLC customers in the DBP programs accounting for the largest portions of estimated load impacts (see last column in Table 3.3).

Table 3.3. Number of CBP and DBP Customer Accounts, Their Average Size, and Average Hourly Load Impacts (2009) – *HVLC and Non-HVLC*

		# of Customers			Average Maximum Demand (kW)		2009 Load Impacts (MW)		
Utility	Program	Non-HVLC	HVLC	% HVLC	Non-HVLC	HVLC	Non-HVLC	HVLC	% HVLC
PG&E	CBP	715	243	25%	347	287	32.9	7.6	19%
	DBP	729	287	28%	1,358	1,298	69.3	20.2	23%
SCE	CBP	591	44	7%	283	591	24.0	2.4	9%
	DBP	202	210	51%	1,725	1,330	12.9	18.9	60%
SDG&E	CBP	225	22	9%	308	1,155	13.5	2.4	15%
	Total	2,462	806		741	959	152.7	51.6	
	Shares	75%	25%				75%	25%	

As shown in Table 3.4, the average load factor of HVLC customers is approximately half that of non-HVLC customers (32 percent compared to 59 percent). The average baseline error (as measured by the RRMSE, or U-Statistic) of HVLC customers is substantially higher than that of non-HVLC customers (48 percent compared to 8 percent overall).

The differences in baseline error due to HVLC type do not directly translate to percentage credit payment errors, as the customer incentives vary by program type. For DBP, the incentive payments are based solely on energy performance during events, so the percent payment errors for HVLC customers with high baseline errors are substantially greater than those for non-HVLC. The baseline errors for HVLC customers in the CBP do not necessarily affect incentives as greatly, due to the split of incentives between energy performance during events that are tied to the baseline, and capacity "standby" payments that are provided for CBP even if no events are called. The relatively strong restrictions on performance payments of the CBP capacity credits during events also act as a disincentive for poor performance, with most CBP participants working within an aggregated group which tends to mute individual underperformance.

[21] One of SDG&E's CBP customers identified as HVLC was a very large customer, which increased the average size for HVLC substantially.

Table 3.4. Average Load Factor, Baseline Error, and Credit Payment Error – *HVLC and Non-HVLC*

		Load Factor		Baseline Error (RRMSE)		Average % Credit Payment Error	
Utility	Program	Non-HVLC	HVLC	Non-HVLC	HVLC	Non-HVLC	HVLC
PG&E	CBP	56%	31%	9%	61%	-51%	-67%
	DBP	61%	33%	9%	40%	-19%	-44%
SCE	CBP	61%	43%	5%	90%	-48%	-61%
	DBP	60%	31%	10%	37%	-6%	-36%
SDG&E	CBP	59%	27%	7%	40%	-41%	-70%
	Total	59%	32%	8%	48%	-36%	-50%

3.3.2 Differences in HVLC and non-HVLC characteristics by industry group

Tables 3.5 through 3.10 show the differences in HVLC and non-HVLC characteristics by program and industry group. Tables 3.5 and 3.6 show that Industry Groups 1, 3, and 6 have the highest proportions of HVLCs for both CBP and DBP.

Table 3.5. Number of Customer Accounts and Average Hourly Load Impacts (2009), by Industry Type & HVLC and Non-HVLC – *CBP*

	# of Customers			Load Impacts (MW)	
Industry Group	Non-HVLC	HVLC	% HVLC	Non-HVLC	HVLC
1. Agriculture, Mining & Construction	11	39	78%	9.96	1.94
2. Manufacturing	97	49	34%	19.00	2.46
3. Wholesale, Transport, other Utilities	43	58	57%	1.39	3.79
4. Retail stores	888	27	3%	30.67	0.51
5. Offices, Hotels, Health, Services	354	41	10%	7.69	0.63
6. Schools	21	47	69%	1.54	3.02
7. Gov't, Entertainment, Other Services	107	44	29%	0.22	0.07
8. Other/Unknown	10	4	29%	-0.02	0.00
Total	1,531	309	17%	70.5	12.4
Share	83%	17%		85%	15%

Table 3.6. Number of Customer Accounts and Average Hourly Load Impacts (2009), by Industry Type & HVLC and Non-HVLC – *DBP*

	# of Customers			Load Impacts (MW)	
Industry Group	Non-HVLC	HVLC	% HVLC	Non-HVLC	HVLC
1. Agriculture, Mining & Construction	43	80	65%	0.92	0.02
2. Manufacturing	277	114	29%	68.59	34.04
3. Wholesale, Transport, other Utilities	102	138	58%	3.44	5.23
4. Retail stores	82	13	14%	0.34	0.00
5. Offices, Hotels, Health, Services	294	20	6%	7.64	0.00
6. Schools	27	120	82%	0.36	-0.13
7. Gov't, Entertainment, Other Services	105	12	10%	0.92	0.00
8. Other/Unknown	1	0	0%	0.00	n/a
Total	931	497	35%	82.2	39.2
Share	65%	35%		68%	32%

Table 3.7. Average Load Factor and Size, by Industry Type & HVLC and Non-HVLC – *CBP*

Industry Group	Load Factor		Maximum Demand (kW)	
	Non-HVLC	HVLC	Non-HVLC	HVLC
1. Agriculture, Mining & Construction	59%	31%	2,228	458
2. Manufacturing	57%	34%	789	525
3. Wholesale, Transport, other Utilities	56%	43%	173	372
4. Retail stores	61%	39%	271	250
5. Offices, Hotels, Health, Services	55%	27%	274	362
6. Schools	51%	25%	1,177	647
7. Gov't, Entertainment, Other Services	53%	28%	122	86
8. Other/Unknown	55%	28%	148	33
Total	58%	33%	317	392

Table 3.8. Average Load Factor and Size, by Industry Type & HVLC and Non-HVLC – *DBP*

Industry Group	Load Factor		Maximum Demand (kW)	
	Non-HVLC	HVLC	Non-HVLC	HVLC
1. Agriculture, Mining & Construction	58%	21%	3,578	748
2. Manufacturing	65%	41%	2,096	3,452
3. Wholesale, Transport, other Utilities	62%	39%	855	1,001
4. Retail stores	59%	34%	296	247
5. Offices, Hotels, Health, Services	59%	28%	1,076	397
6. Schools	46%	22%	1,365	313
7. Gov't, Entertainment, Other Services	57%	28%	1,323	951
8. Other/Unknown	51%	n/a	296	n/a
Total	61%	32%	1,438	1,311

Tables 3.9 and 3.10 show differences in baseline errors and average percent credit payment errors, by industry group and HVLC status. For CBP customers in industry group 3, there is a very large difference in the average baseline error for HVLC and non-HVLC customers. The differences are consistent, but smaller in magnitude for the other industry groups and DBP customers. The two right-most columns show that the average credit payment errors are somewhat similar across industry groups, with HVLC payment errors being larger than non-HVLC payment errors.

Table 3.9. Average Baseline Error and % Credit Payment Error, by Industry Type & HVLC and Non-HVLC -- *CBP*

Industry Group	Baseline Error (RRMSE)		Average % Credit Payment Error	
	Non-HVLC	HVLC	Non-HVLC	HVLC
1. Agriculture, Mining & Construction	12%	47%	-52%	-59%
2. Manufacturing	12%	36%	-51%	-61%
3. Wholesale, Transport, other Utilities	14%	167%	-52%	-64%
4. Retail stores	5%	27%	-47%	-74%
5. Offices, Hotels, Health, Services	8%	37%	-50%	-66%
6. Schools	8%	28%	-50%	-73%
7. Gov't, Entertainment, Other Services	12%	62%	-55%	-71%
8. Other/Unknown	11%	53%	-48%	-69%
Total	7%	64%	-48%	-66%

Table 3.10. Average Baseline Error and % Credit Payment Error, by Industry Type & HVLC and Non-HVLC -- *DBP*

Industry Group	Baseline Error (RRMSE)		Average % Credit Payment Error	
	Non-HVLC	HVLC	Non-HVLC	HVLC
1. Agriculture, Mining & Construction	15%	45%	-14%	-44%
2. Manufacturing	9%	31%	-14%	-34%
3. Wholesale, Transport, other Utilities	13%	56%	-18%	-40%
4. Retail stores	6%	28%	-11%	-50%
5. Offices, Hotels, Health, Services	7%	41%	-19%	-35%
6. Schools	10%	23%	-25%	-44%
7. Gov't, Entertainment, Other Services	8%	28%	-14%	-39%
8. Other/Unknown	18%	n/a	-27%	n/a
Total	9%	39%	-16%	-40%

3.4 Develop Tool for HVLC Screening

We developed a tool for identifying customers who meet the HVLC criterion by estimating a logit regression model that predicts the likelihood of meeting the HVLC criterion based on a short list of readily available customer characteristics. As noted above, the focus on load variability suggests a criterion based on measured load variability, such as the average CV. However, we can approximate the likelihood of the average CV exceeding the criterion by using related information from available billing data.

To establish the relationship between average CV and other available information we estimate a logit regression model that can be used to predict the likelihood that the criterion of an average CV of 30 percent is exceeded. Results of model estimation are shown in Table 3.11. The Pseudo-R^2 for the equation is 0.55.[22] Negative coefficients indicate that the variable in question *reduces* the probability that the customer is an HVLC, while positive coefficients indicate that the variable *increases* the probability.

[22] Since logit equations are non-linear, the standard R^2 statistic of linear regression equations is not available. However, the pseudo- R^2 value that may be calculated from the results of the estimation provides an analogous measure of goodness of fit.

Variables with negative and significant coefficients include the following (industry group coefficients are relative to the omitted Industry Group 2, which is Manufacturing): membership in Industry Groups 4 (Retail stores), 5 (Offices, Hotels, etc.) and 7 (Entertainment, Govt., etc.); and load factor. Variables with positive and significant coefficients include Industry Group 1 (Agriculture, Mining, and Construction), the Water Utility industry subgroup (a subset of Industry 3) and size, as measured by the natural log of the customer's maximum demand.

It is clear that (low) load factor is a strong predictor of HVLC. However, it is not feasible to use a specific value of load factor in isolation as the HVLC criterion. However, used in conjunction with industry type, it provides a useful indicator, as described below.[23]

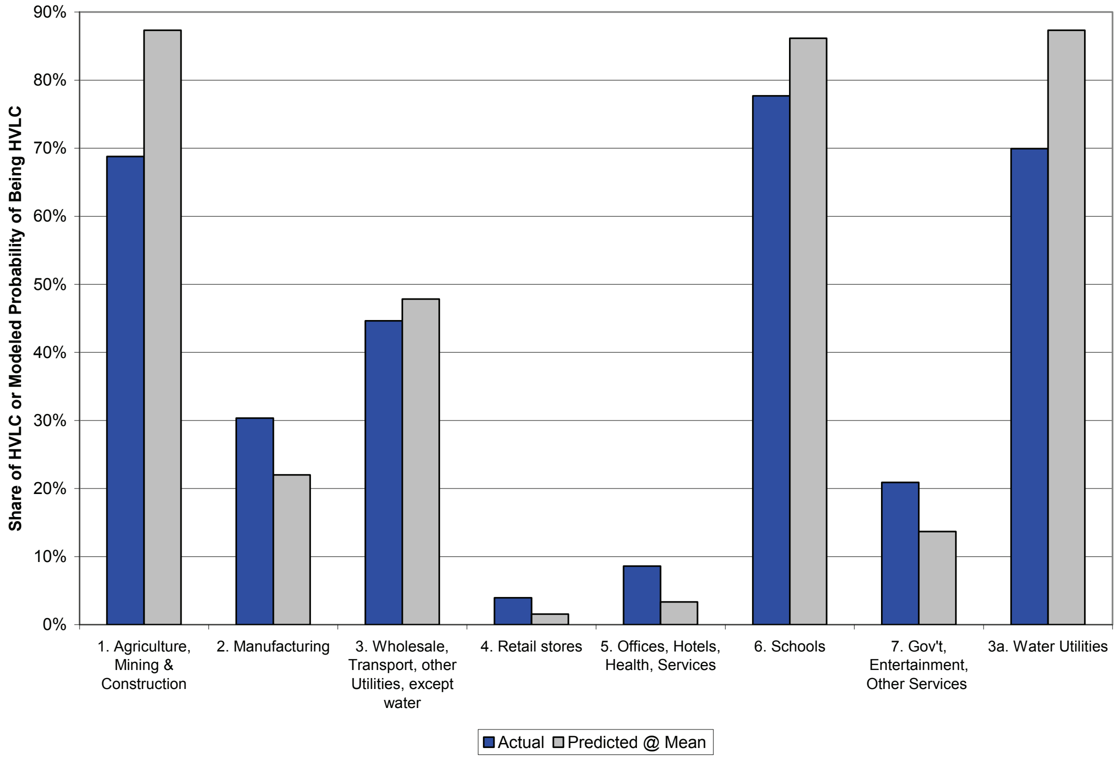
Table 3.11. Logit Model Parameters for Predicting HVLCs

Variable	Coefficient	Standard Error	z-statistic
Industry Group 1	0.711	0.277	2.57
Industry Group 3 (not water)	0.274	0.250	1.10
Industry Group 4	-2.039	0.229	-8.92
Industry Group 5	-2.103	0.215	-9.76
Industry Group 6	0.009	0.252	0.03
Industry Group 7	-1.197	0.242	-4.95
Water Utility	2.768	0.284	9.75
ln(Max kW)	0.176	0.048	3.64
Load Factor	-12.154	0.553	-21.99
Constant	4.184	0.366	11.43

Figure 3.2 shows actual and predicted values (at the mean values of the explanatory variables) of the probability of being classified as HVLC. The figure shows differences across industry group of the probabilities of HVLC. (The figure does not really measure accuracy of the logit predictions, since it shows values at *mean* values of the explanatory variables rather than for each customer's actual values.)

[23] We explored models that interacted load factor and industry type, but the results did not improve upon the independent effects of those factors.

Figure 3.2. Actual and Predicted (at Mean Values of Explanatory Variables) Values of Probability of HVLC, by Industry Group



To provide an indication of model accuracy, Table 3.12 shows the average predicted probability of labeling a customer as HVLC, by actual HVLC status (zero for not HVLC, and 1 for HVLC). Results are shown by industry group. If the model predicted perfectly, all values in the far right column would be 100%, and all values in the middle column would be 0%. The model does well, in the sense that the predicted probabilities are always much higher for the actual HVLC customers than for the non-HVLC customers. However, the model does not always provide a reliable indicator of when a customer is likely to be HVLC. For example, the model does not appear to do a very good job of identifying HVLC customers in Industry Group 4 (Retail Stores), as the average predicted probability for those customers is only 27 percent. At the same time, the fraction of HVLC customers in those industry groups is generally quite small, thus suggesting that predicting HVLC occurrence for those industry types is difficult, but relatively unimportant.

Table 3.12. Predicted Probabilities from the HVLC Logit Model, by Industry Group

Industry Group	HVLC=0	HVLC=1
Industry Group 1	34%	84%
Industry Group 2	17%	60%
Industry Group 3 (not water)	28%	66%
Industry Group 4	3%	27%
Industry Group 5	5%	43%
Industry Group 6	40%	89%
Industry Group 7	11%	57%
Water Utility	47%	80%

An Excel-based HVLC screening tool has been developed from the logit model shown in Table 3.12. The model calculates a customer's predicted probability of being an HVLC based on user-entered values for the customer's industry group, load factor, and maximum demand. Higher predicted probabilities are associated with a greater likelihood that the customer is an HVLC. This tool may be used by the utilities to identify customers who are more likely to be HVLCs. If the resulting predicted probability exceeds a certain threshold (based on the user's judgment), further investigation can be conducted into the customer's load profile characteristics.

4. ASSESSMENT OF DAY-OF BASELINE ADJUSTMENT FACTORS

This element of the study addresses the issue of the appropriate magnitude of the cap on the day-of adjustment to the 10-in-10 baseline, and the number of customer accounts that may exceed the cap. Current utility plans are to offer the adjusted baseline as an option in the CBP program, and to limit upward and downward adjustments to no more than 20 percent.

The objectives of this portion of the study include: 1) to determine the portion of customers whose day-of adjustment factors reach or exceed the 20 percent adjustment cap (differentiating between customers who selected the adjustment baseline and those that did not), and 2) to measure how often that cap is binding for each customer. The utilities offered the use of data from the 2010 program year (through August) for the CBP programs, plus SDG&E’s DSP program.

4.1 Data Collection and Validation

To address the third objective, we needed customer characteristics and interval load data for 2010. We prepared a data request memorandum for the utilities specifying the required information. The required information will include:

- Enrolled *customer account* information, including:
  - a Customer ID that is consistent across databases;
  - rate schedule;
  - NAICS or SIC code;
  - key billing determinants (maximum demand and annual kWh);
  - climate zone;

- CAISO local capacity area; and
- program enrollment date and departure dates (if applicable) for all DR programs in which the customers participate.

- Billing-based *interval load data* for June through August 2010 for each enrolled customer;
- For each aggregator—Database of enrolled customers (SAID # and other relevant ID #s) nominated for each CBP (and DSP) program type (*e.g.*, day-of, day-ahead, hours of curtailment), by month; and
- Event dates and hours for each aggregator and program type, for each test and actual event.

We examined the data to ensure that the customer information could be matched to hourly load data and event data.

4.2 Day-of Adjustment Factor Calculations

We first used customer-level hourly interval load data, along with customer enrollment and event data, to calculate the 10-in-10 baseline for each CBP and DSP customer and event at each utility. 10-in-10 baselines were derived using the first 10 non-holiday, non-event weekdays preceding the event. We then computed the day-of adjustment factors for each customer and event at each utility using the ratio of the average load on the event day to the average load in the 10-in-10 baseline, averaging over the 4th, 3rd, and 2nd hour preceding the start of the event, where we accounted for each customer's program type and event start time.

Adjustment factors were computed for each event day, as well as for an additional series of simulated-event days. Seven simulated event days were selected for each program from the days of highest system load in the summer of 2009 that were not called as CBP or DBP event days. In most cases, actual events were called on at least the three or four highest-load days, and in some cases more (*e.g.*, the nine highest-load days for SDG&E's day-of CBP). As a result, simulated event days typically occurred on days of lower system load and average temperatures than actual event days. Differences between adjustment factors on simulated-event days and on actual event days could potentially result from two primary factors. One is that on actual events some customers may take pre-event actions such as pre-cooling that may affect their day-of adjustment factors. Another is that weather conditions are generally more severe on the actual event days than on the simulated event days, which could result in higher day-of adjustment factors than for simulated events.

4.3 Distributions of Day-of Baseline Adjustments

We begin by summarizing aggregate results regarding the magnitude of baseline adjustments for those CBP customers who selected the adjustment option in 2010, and then provide detailed results that differentiate among several factors, including customers' choice of the baseline adjustment option, actual vs. simulated event types, and industry type.

4.3.1 Aggregate results

Table 4.1 shows the percentage of CBP customers who selected the adjusted baseline option for the three utilities (first row) and then summarizes the following three high-level results for those customers, for both actual and simulated, or pseudo events:[24]

- The percentage of those customer accounts whose baseline adjustment was constrained by the 20 percent cap for at least one event (second row);
- The percentage of customer-events (*i.e.*, the number of customers times the number of events in which they participated) in which the 20 percent cap was exceeded by a customer for an event (third row); and
- The average percent of events per customer for which the baseline adjustment was constrained by the 20 percent cap (last row).

From 36 to 73 percent of customers across the three CBP programs selected the day-of adjustment option. Of those customers, more than half had adjustments that exceeded the 20 percent cap for at least one actual event, and somewhat fewer reached the cap on the simulated events. Overall, the adjustments for about 30 to 40 percent of all customer-events for those customers selecting the adjustment option exceeded the 20 percent cap, while 20 percent or less did so for the simulated events. Finally, for those customers whose adjustments exceeded the cap at least once, they did so for 50 to 60 percent of the actual events, and 30 to 40 percent of the simulated events.

Table 4.1. Overall Percentages of Occurrences of Exceeding 20 Percent Cap

	PG&E CBP		SCE CBP		SDG&E CBP	
	Actual	Sim	Actual	Sim	Actual	Sim
% of Customers selecting BL adjustment option	36%	36%	47%	47%	73%	73%
% of Customers who (ever) exceeded 20% cap	56%	42%	55%	45%	55%	38%
% of Customer-events that exceeded cap	36%	13%	38%	20%	29%	14%
Ave. % of evts. per cust. where cap exceeded	63%	31%	69%	44%	52%	36%

Table 4.2 provides additional detail on the range of baseline adjustments for both those customer accounts that did and did not select the adjusted baseline option, and for both the actual CBP program events and the simulated events. Results for DSP are shown in Table 4.3.[25] The following are observations on the ranges of baseline adjustments:

- Adjustment factors of *greater* than the 20 percent cap were substantially more frequent than *downward* adjustments of more than 20 percent (32 percent versus 4 percent overall for actual events, for those selecting the adjustment option).
- Adjustment factors exceeding 20 percent were more frequent for the *actual* events compared to the *simulated*, or pseudo-events, for those customers who selected the adjustment option (32 percent overall compared to 15 percent).
- Adjustment factors exceeding 20 percent were somewhat more frequent for customer accounts *choosing the adjustment option* than for those *not choosing* it (*e.g.*, 32 percent overall compared to 24 percent, for the actual events).

[24] An adjusted baseline option was not available for SDG&E's DSP customers, so no results are provided at this level of aggregation.

[25] The actual program baseline for DSP in 2010 was the unadjusted 3-in-10 method. However, the day-of adjustment results in the table were calculated using the 10-in-10 baseline.

- Adjustment factors exceeding 20 percent for DSP customers were considerably more frequent for both actual and simulated events than those for CBP customers in total (*e.g.*, 43 percent versus 24 percent for actual events).

Table 4.2. Distributions of Day-of Baseline Adjustment Factors by Utility, Event Type, and Choice of Adjustment Option – *CBP*

		Event	Adjustment	-20% to +20% BL Adjustment		
Utility	**Program**	**Type**	**Option**	**Below**	**Within**	**Above**
All	All	Actual	Yes	4%	64%	32%
PGE	CBP	Actual	Yes	9%	56%	36%
SCE	CBP	Actual	Yes	1%	60%	38%
SDGE	CBP	Actual	Yes	3%	68%	29%
All	All	Actual	No	9%	67%	24%
PGE	CBP	Actual	No	12%	60%	28%
SCE	CBP	Actual	No	1%	79%	20%
SDGE	CBP	Actual	No	12%	71%	17%
All	All	Pseudo	Yes	7%	79%	15%
PGE	CBP	Pseudo	Yes	9%	78%	13%
SCE	CBP	Pseudo	Yes	7%	74%	20%
SDGE	CBP	Pseudo	Yes	4%	82%	14%
All	All	Pseudo	No	8%	79%	13%
PGE	CBP	Pseudo	No	10%	79%	11%
SCE	CBP	Pseudo	No	1%	83%	16%
SDGE	CBP	Pseudo	No	11%	76%	13%

Table 4.3. Distributions of Day-of Baseline Adjustment Factors by Event Type – *DSP*

		Event	Adjustment	-20% to +20% BL Adjustment		
Utility	**Program**	**Type**	**Option**	**Below**	**Within**	**Above**
SDGE	DSP	Actual	No	13%	44%	43%
SDGE	DSP	Pseudo	No	15%	55%	30%

In response to a question from one of the reviewers, we also calculated adjustment factors for aggregated CBP loads, by aggregator and choice of adjustment option (*i.e.*, customer loads for a given aggregator were aggregated separately for those who chose and did not choose the day-of adjustment option. Table 4.4 summarizes the ranges of adjustment factors at the program level based on the aggregated loads. Comparing the results with those in Table 4.2 for the individual customer adjustment factors indicates that the percentage of day-of adjustments exceeding 20 percent for the aggregated loads is often, but not always less than that for the individual customers.[26]

[26] Adjustment factor results were calculated for each aggregator but are not reported here. In many cases, results varied considerably across aggregators.

Table 4.4. Distributions of Day-of Baseline Adjustment Factors by Utility, Event Type, and Choice of Adjustment Option – *CBP (Aggregator-level Loads)*

		Event	Adjustment	-20% to +20% BL Adjustment		
Utility	Program	Type	Option	Below	Within	Above
PGE	CBP	Actual	Yes	12%	64%	24%
SCE	CBP	Actual	Yes	0%	62%	38%
SDGE	CBP	Actual	Yes	3%	58%	39%
PGE	CBP	Actual	No	0%	80%	20%
SCE	CBP	Actual	No	1%	79%	20%
SDGE	CBP	Actual	No	13%	85%	3%
PGE	CBP	Pseudo	Yes	8%	91%	2%
SCE	CBP	Pseudo	Yes	8%	87%	5%
SDGE	CBP	Pseudo	Yes	4%	73%	23%
PGE	CBP	Pseudo	No	5%	93%	3%
SCE	CBP	Pseudo	No	3%	79%	18%
SDGE	CBP	Pseudo	No	9%	80%	11%

4.3.2 Detailed results on baseline adjustment factors

Tables 4.5 through 4.12 provide further details on full distributions of adjustment factors by industry group for each program, including SDG&E's DSP, for both actual and simulated events, and for those customers who selected the adjusted baseline option and those who did not. Following those tables are a series of graphs that provide a more convenient visual presentation of the results in the tables. In the graphs, the height of each bar represents the percentage of customer accounts in the relevant industry/adjustment-choice whose day-of adjustment values lie within the indicated ranges.[27] Distributions are shown by industry type and in total.

[27] In the figures, the adjustment factor is (1 + Day-of Adjustment), such that a value of 1.0 indicates a zero adjustment, while 1.2 indicates a positive 20 percent adjustment.

Table 4.5. Distributions of Baseline Adjustment Factors – PGE CBP *Actual Events*

Ind Group	Adj BL?	< 0.6	0.6 - 0.7	0.7 - 0.8	0.8 - 0.9	0.9 - 1.0	1.0 - 1.1	1.1 - 1.2	1.2 - 1.3	1.3 - 1.4	> 1.4	Total > 1.2
2	Yes	6%	1%	0%	4%	15%	32%	24%	9%	1%	7%	17%
3	Yes	9%	3%	5%	6%	12%	27%	18%	9%	6%	6%	20%
4	Yes	1%	0%	0%	1%	3%	25%	27%	21%	12%	11%	44%
5	Yes	0%	0%	1%	2%	12%	32%	26%	12%	12%	4%	27%
6	Yes	18%	4%	0%	0%	0%	14%	25%	7%	11%	21%	39%
7	Yes	13%	0%	0%	0%	13%	27%	23%	20%	0%	3%	23%
Total	Yes	3%	1%	1%	2%	6%	26%	25%	17%	9%	9%	36%
2	No	6%	0%	5%	9%	16%	25%	11%	6%	7%	15%	28%
3	No	8%	4%	4%	7%	18%	24%	13%	4%	1%	17%	22%
4	No	2%	1%	1%	2%	11%	36%	22%	12%	6%	7%	26%
5	No	1%	1%	2%	7%	20%	24%	15%	11%	8%	12%	31%
6	No	15%	3%	3%	3%	13%	16%	9%	8%	9%	20%	38%
7	No	4%	1%	4%	8%	16%	24%	13%	9%	7%	14%	30%
Total	No	3%	1%	2%	5%	15%	28%	17%	10%	7%	11%	28%

Table 4.6. Distributions of Baseline Adjustment Factors – PGE CBP *Simulated Events*

Ind Group	Adj BL?	< 0.6	0.6 - 0.7	0.7 - 0.8	0.8 - 0.9	0.9 - 1.0	1.0 - 1.1	1.1 - 1.2	1.2 - 1.3	1.3 - 1.4	> 1.4	Total > 1.2
2	Yes	2%	2%	3%	7%	21%	36%	18%	4%	3%	5%	11%
3	Yes	8%	3%	5%	7%	17%	27%	11%	10%	5%	5%	20%
4	Yes	1%	0%	0%	1%	19%	51%	17%	5%	2%	2%	9%
5	Yes	0%	0%	1%	2%	26%	49%	14%	4%	2%	0%	7%
6	Yes	14%	0%	0%	2%	4%	33%	20%	16%	8%	2%	27%
7	Yes	13%	0%	0%	8%	23%	33%	15%	8%	0%	0%	8%
Total	Yes	2%	1%	1%	3%	20%	46%	17%	6%	3%	2%	11%
2	No	3%	1%	2%	8%	18%	33%	8%	9%	9%	9%	27%
3	No	9%	1%	4%	3%	21%	28%	15%	7%	5%	7%	19%
4	No	2%	1%	0%	2%	23%	49%	16%	5%	1%	1%	7%
5	No	1%	1%	2%	6%	24%	40%	16%	6%	2%	3%	11%
6	No	8%	8%	5%	8%	14%	25%	12%	6%	7%	8%	20%
7	No	4%	2%	2%	9%	20%	33%	15%	8%	3%	3%	14%
Total	No	3%	1%	2%	5%	23%	41%	15%	6%	2%	3%	11%

Table 4.7. Distributions of Baseline Adjustment Factors – SCE CBP *Actual Events*

Ind Group	Adj BL?	< 0.6	0.6 - 0.7	0.7 - 0.8	0.8 - 0.9	0.9 - 1.0	1.0 - 1.1	1.1 - 1.2	1.2 - 1.3	1.3 - 1.4	> 1.4	Total > 1.2
2	Yes	0%	22%	0%	22%	22%	0%	11%	0%	11%	11%	22%
3	Yes	8%	0%	0%	8%	8%	33%	0%	0%	17%	25%	42%
4	Yes	0%	0%	0%	0%	4%	22%	36%	21%	12%	5%	38%
5	Yes	0%	0%	1%	1%	6%	20%	34%	22%	10%	8%	39%
6	Yes	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%	100%
7	Yes	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Total	Yes	0%	0%	0%	1%	5%	21%	34%	21%	11%	6%	38%
2	No	11%	0%	0%	0%	11%	0%	11%	0%	22%	44%	67%
3	No	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
4	No	0%	0%	0%	0%	4%	44%	31%	11%	4%	4%	20%
5	No	0%	0%	0%	0%	17%	50%	33%	0%	0%	0%	0%
6	No	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
7	No	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Total	No	0%	0%	0%	0%	4%	44%	31%	11%	4%	4%	20%

Table 4.8. Distributions of Baseline Adjustment Factors – SCE CBP *Simulated Events*

Ind Group	Adj BL?	< 0.6	0.6 - 0.7	0.7 - 0.8	0.8 - 0.9	0.9 - 1.0	1.0 - 1.1	1.1 - 1.2	1.2 - 1.3	1.3 - 1.4	> 1.4	Total > 1.2
2	Yes	0%	33%	33%	0%	0%	33%	0%	0%	0%	0%	0%
3	Yes	8%	0%	0%	0%	8%	17%	8%	8%	25%	25%	58%
4	Yes	6%	1%	1%	0%	4%	31%	38%	15%	3%	1%	19%
5	Yes	1%	1%	0%	1%	5%	30%	45%	15%	2%	2%	19%
6	Yes	0%	0%	0%	0%	0%	20%	20%	0%	20%	40%	60%
7	Yes	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Total	Yes	5%	1%	1%	0%	4%	31%	39%	14%	3%	2%	20%
2	No	20%	20%	0%	0%	20%	0%	0%	0%	40%	0%	40%
3	No	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
4	No	0%	0%	0%	0%	7%	53%	24%	11%	3%	2%	16%
5	No	0%	0%	0%	0%	17%	17%	33%	33%	0%	0%	33%
6	No	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
7	No	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Total	No	0%	0%	0%	0%	7%	52%	24%	11%	3%	2%	16%

Table 4.9. Distributions of Baseline Adjustment Factors – SDG&E CBP *Actual Events*

Ind Group	Adj BL?	< 0.6	0.6 - 0.7	0.7 - 0.8	0.8 - 0.9	0.9 - 1.0	1.0 - 1.1	1.1 - 1.2	1.2 - 1.3	1.3 - 1.4	> 1.4	Total > 1.2
2	Yes	0%	0%	0%	0%	0%	0%	67%	22%	11%	0%	33%
3	Yes	11%	1%	5%	5%	14%	22%	7%	4%	5%	26%	35%
4	Yes	1%	0%	0%	0%	2%	37%	35%	16%	6%	4%	26%
5	Yes	2%	0%	2%	2%	17%	36%	17%	9%	4%	12%	25%
6	Yes	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
7	Yes	0%	0%	0%	1%	13%	17%	20%	25%	12%	12%	49%
Total	Yes	1%	0%	1%	1%	7%	34%	28%	15%	6%	7%	29%
2	No	5%	0%	3%	6%	13%	33%	29%	5%	3%	5%	12%
3	No	26%	2%	2%	13%	15%	20%	14%	2%	3%	4%	9%
4	No	0%	0%	0%	0%	3%	76%	15%	4%	2%	0%	6%
5	No	1%	1%	3%	2%	9%	33%	27%	15%	5%	5%	25%
6	No	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
7	No	4%	2%	0%	1%	16%	29%	15%	14%	11%	8%	33%
Total	No	6%	1%	2%	4%	11%	38%	21%	8%	5%	4%	17%

Table 4.10. Distributions of Baseline Adjustment Factors – SDG&E CBP *Simulated Events*

Ind Group	Adj BL?	< 0.6	0.6 - 0.7	0.7 - 0.8	0.8 - 0.9	0.9 - 1.0	1.0 - 1.1	1.1 - 1.2	1.2 - 1.3	1.3 - 1.4	> 1.4	Total > 1.2
2	Yes	0%	0%	0%	0%	14%	43%	43%	0%	0%	0%	0%
3	Yes	16%	3%	1%	10%	10%	27%	3%	7%	4%	19%	30%
4	Yes	1%	0%	0%	1%	11%	60%	20%	5%	1%	2%	8%
5	Yes	1%	1%	1%	2%	16%	41%	16%	8%	4%	10%	22%
6	Yes	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
7	Yes	0%	0%	0%	3%	16%	38%	26%	10%	2%	5%	17%
Total	Yes	1%	0%	1%	1%	13%	51%	19%	7%	2%	5%	14%
2	No	0%	2%	2%	8%	17%	32%	24%	8%	3%	4%	15%
3	No	20%	2%	3%	6%	23%	25%	5%	5%	7%	6%	17%
4	No	0%	0%	0%	0%	10%	84%	5%	1%	0%	0%	1%
5	No	0%	1%	3%	2%	19%	36%	25%	9%	4%	2%	15%
6	No	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
7	No	4%	2%	3%	4%	21%	31%	19%	5%	4%	6%	15%
Total	No	4%	1%	2%	4%	18%	40%	18%	6%	4%	3%	13%

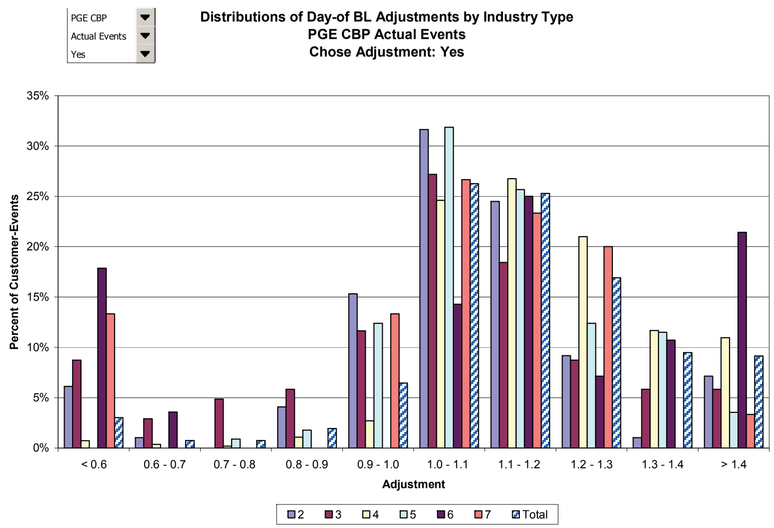
Table 4.11. Distributions of Baseline Adjustment Factors – SDG&E DSP *Actual Events*

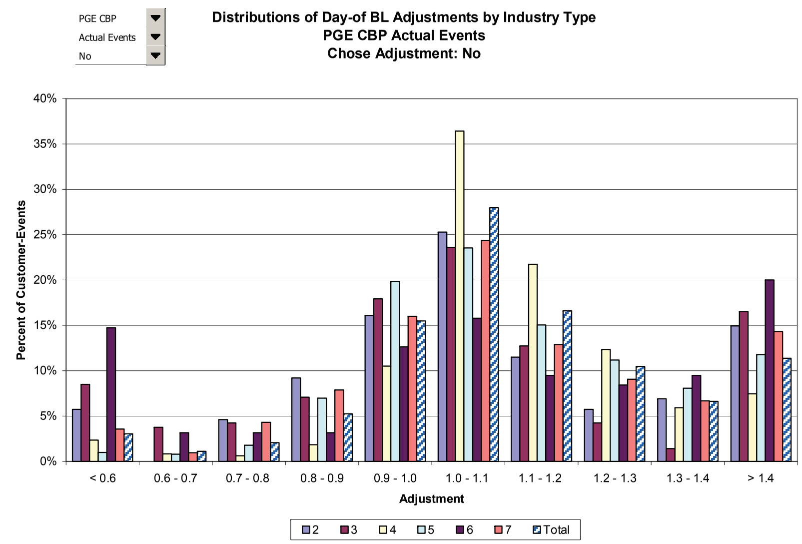
Ind Group	Adj BL?	< 0.6	0.6 - 0.7	0.7 - 0.8	0.8 - 0.9	0.9 - 1.0	1.0 - 1.1	1.1 - 1.2	1.2 - 1.3	1.3 - 1.4	> 1.4	Total > 1.2
2	No	6%	1%	5%	11%	11%	19%	16%	10%	5%	16%	31%
3	No	11%	4%	3%	6%	9%	16%	13%	10%	5%	22%	37%
4	No	0%	0%	0%	1%	7%	37%	32%	17%	5%	1%	23%
5	No	9%	2%	2%	5%	15%	18%	20%	17%	5%	5%	28%
6	No	4%	0%	0%	0%	2%	7%	3%	5%	5%	73%	83%
7	No	0%	0%	0%	7%	7%	43%	30%	7%	7%	0%	13%
Total	No	6%	1%	2%	4%	8%	20%	16%	11%	5%	26%	43%

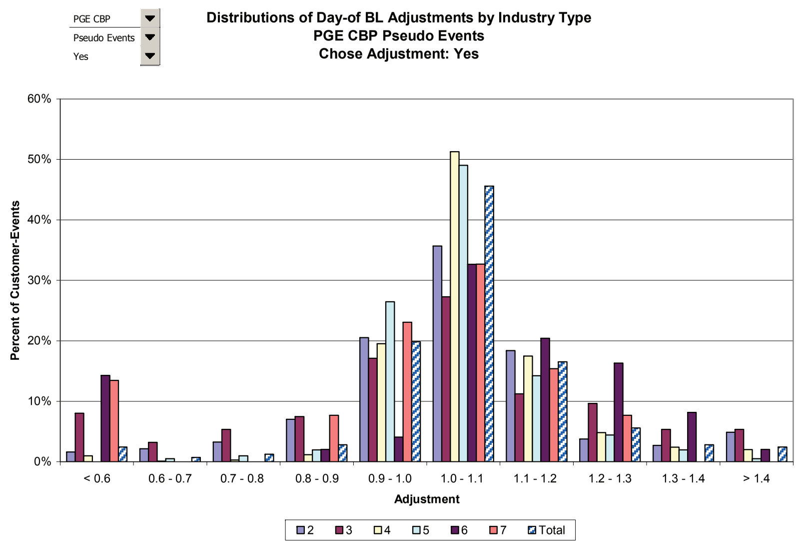
Table 4.12. Distributions of Baseline Adjustment Factors – SDG&E DSP *Simulated Events*

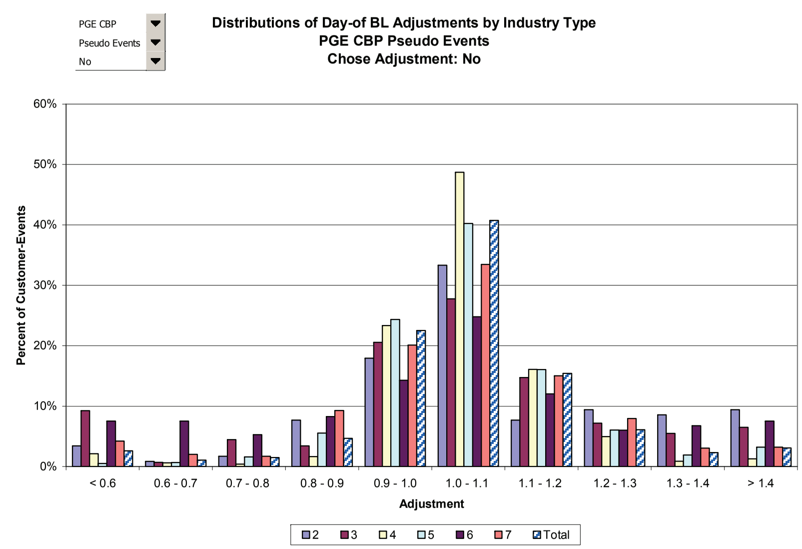
Ind Group	Adj BL?	< 0.6	0.6 - 0.7	0.7 - 0.8	0.8 - 0.9	0.9 - 1.0	1.0 - 1.1	1.1 - 1.2	1.2 - 1.3	1.3 - 1.4	> 1.4	Total > 1.2
2	No	8%	2%	4%	9%	17%	13%	14%	12%	8%	13%	33%
3	No	17%	6%	3%	4%	16%	19%	8%	7%	3%	15%	26%
4	No	0%	0%	0%	0%	15%	62%	18%	3%	1%	0%	4%
5	No	8%	0%	4%	6%	28%	24%	14%	7%	1%	7%	15%
6	No	4%	1%	1%	2%	7%	10%	10%	7%	8%	50%	65%
7	No	0%	0%	0%	8%	29%	38%	17%	8%	0%	0%	8%
Total	No	7%	2%	2%	4%	15%	27%	13%	7%	4%	19%	30%

Figure 4.1. Frequency Distributions of Day-of Adjustments, by Industry Type

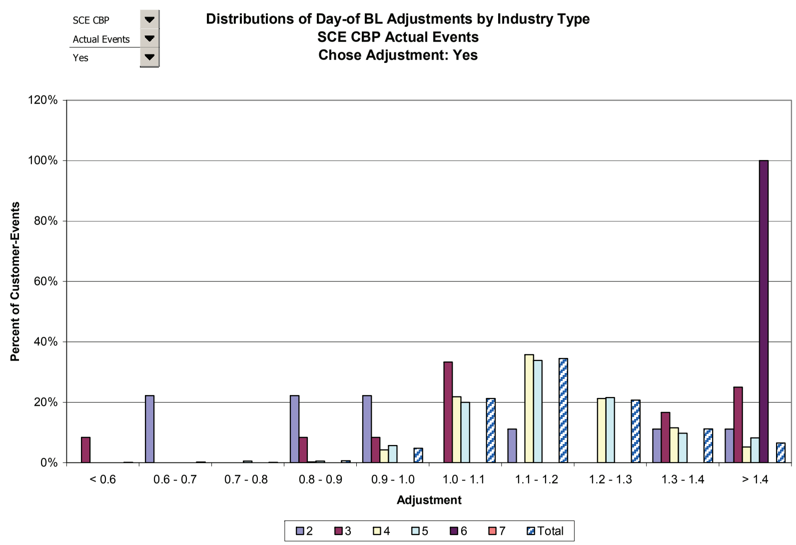




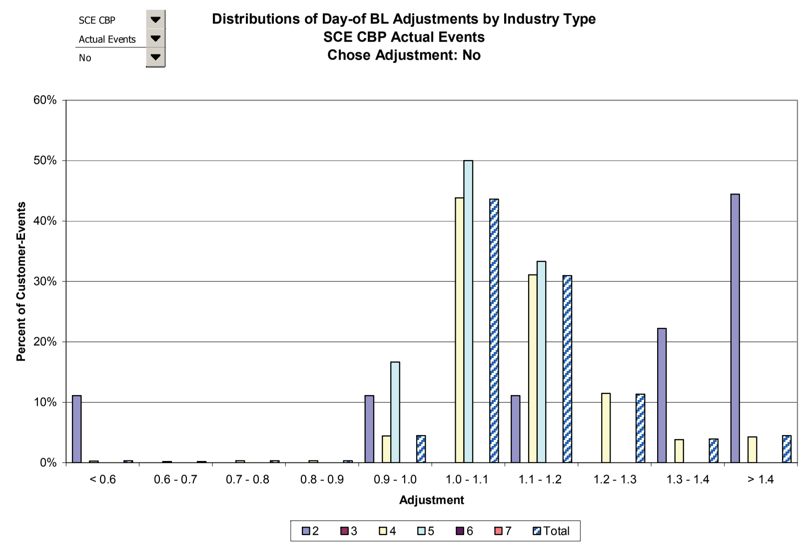




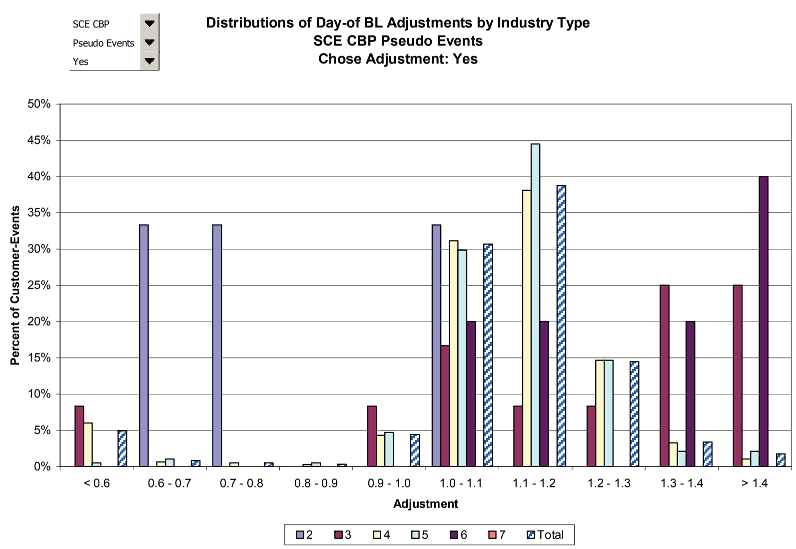
Distributions of Day-of BL Adjustments by Industry Type
SCE CBP Actual Events
Chose Adjustment: Yes



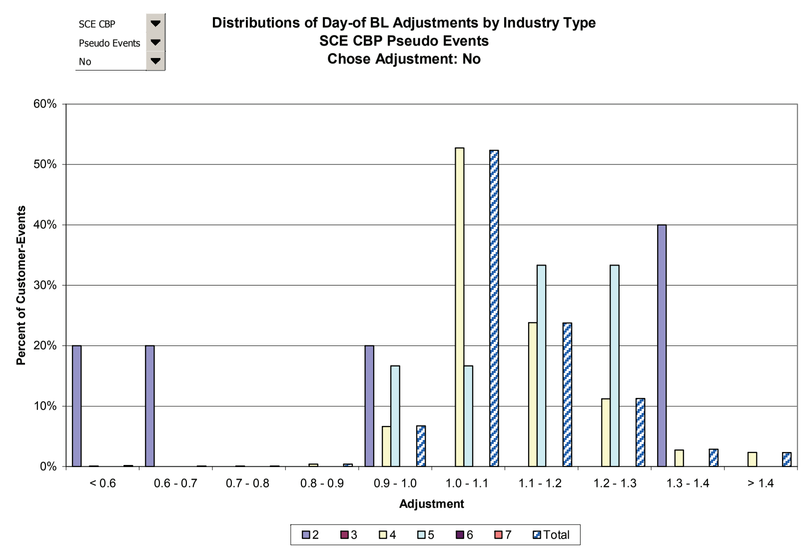
Distributions of Day-of BL Adjustments by Industry Type
SCE CBP Actual Events
Chose Adjustment: No

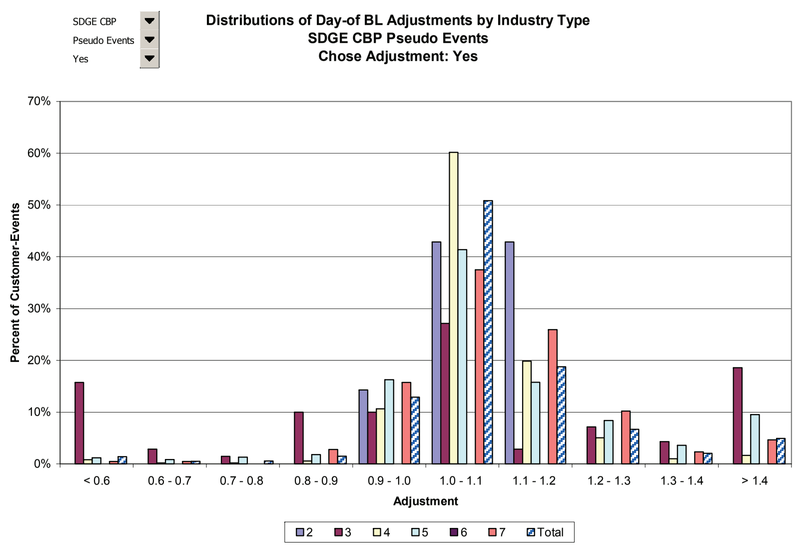


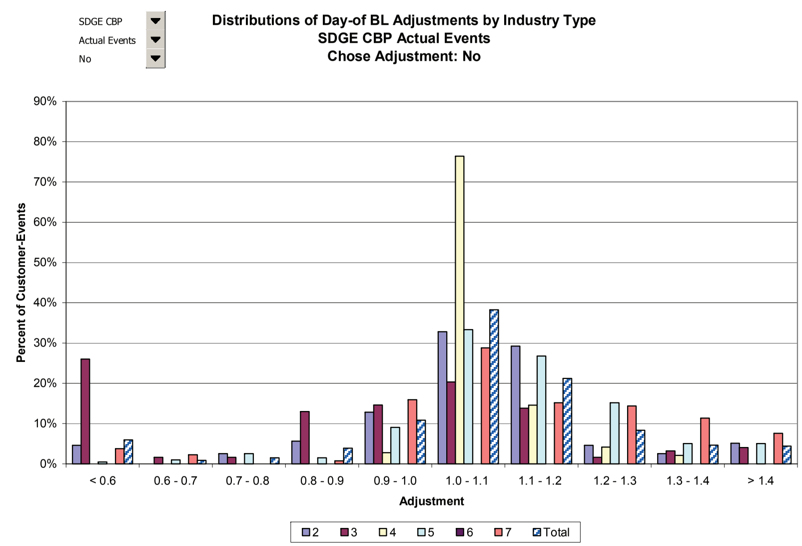
Distributions of Day-of BL Adjustments by Industry Type
SCE CBP Pseudo Events
Chose Adjustment: Yes

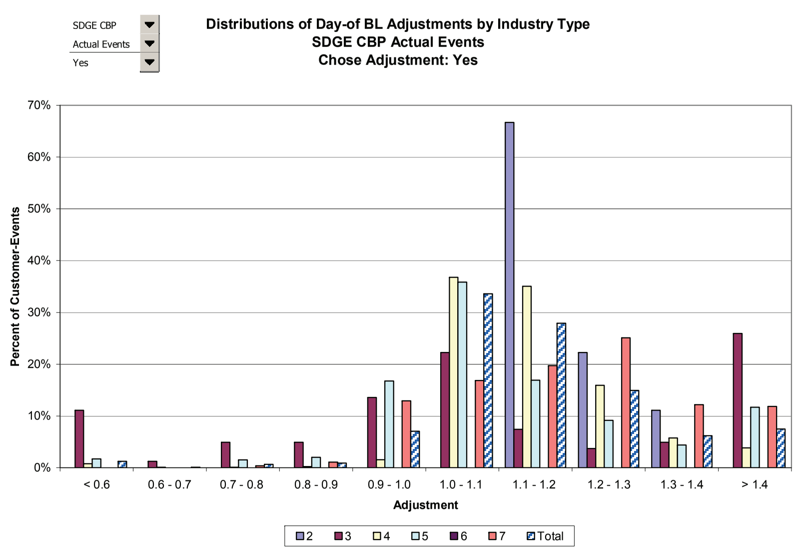


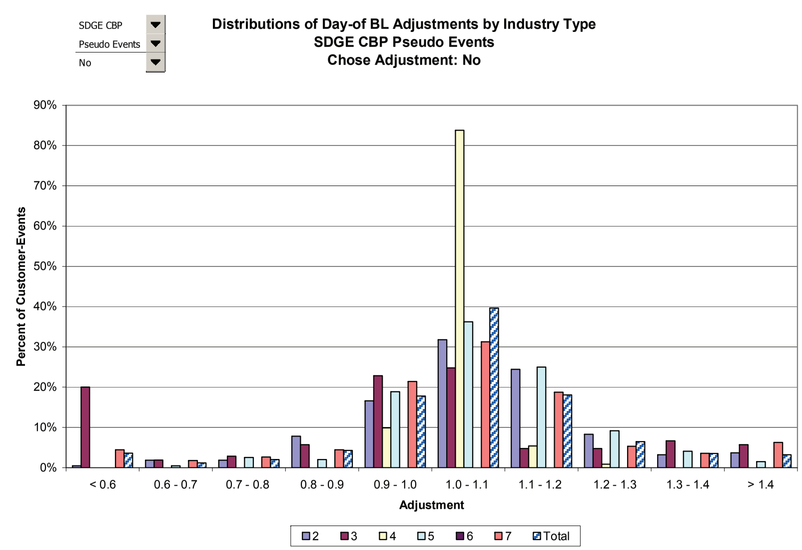
Distributions of Day-of BL Adjustments by Industry Type
SCE CBP Pseudo Events
Chose Adjustment: No

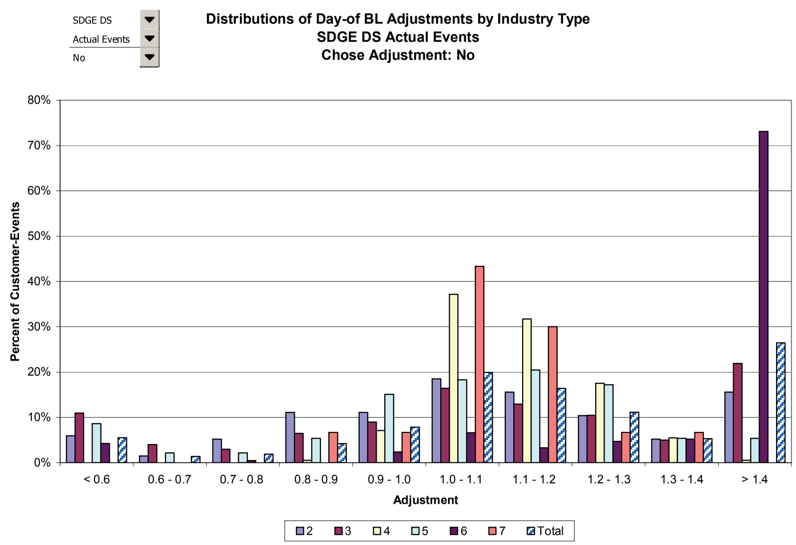


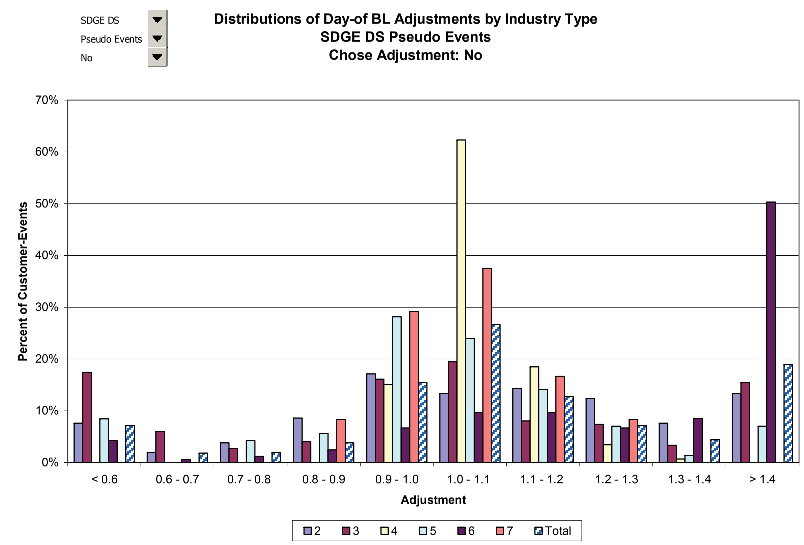

SDGE CBP
Pseudo Events
Yes
Distributions of Day-of BL Adjustments by Industry Type
SDGE CBP Pseudo Events
Chose Adjustment: Yes
Percent of Customer-Events
Adjustment
< 0.6
0.6 - 0.7
0.7 - 0.8
0.8 - 0.9
0.9 - 1.0
1.0 - 1.1
1.1 - 1.2
1.2 - 1.3
1.3 - 1.4
> 1.4
2
3
4
5
6
7
Total


SDGE CBP
Actual Events
No
Distributions of Day-of BL Adjustments by Industry Type
SDGE CBP Actual Events
Chose Adjustment: No
Percent of Customer-Events
Adjustment
< 0.6
0.6 - 0.7
0.7 - 0.8
0.8 - 0.9
0.9 - 1.0
1.0 - 1.1
1.1 - 1.2
1.2 - 1.3
1.3 - 1.4
> 1.4
2
3
4
5
6
7
Total


SDGE CBP
Actual Events
Yes
Distributions of Day-of BL Adjustments by Industry Type
SDGE CBP Actual Events
Chose Adjustment: Yes
Percent of Customer-Events
Adjustment
< 0.6
0.6 - 0.7
0.7 - 0.8
0.8 - 0.9
0.9 - 1.0
1.0 - 1.1
1.1 - 1.2
1.2 - 1.3
1.3 - 1.4
> 1.4
2
3
4
5
6
7
Total


SDGE CBP
Pseudo Events
No
Distributions of Day-of BL Adjustments by Industry Type
SDGE CBP Pseudo Events
Chose Adjustment: No
Percent of Customer-Events
Adjustment
< 0.6
0.6 - 0.7
0.7 - 0.8
0.8 - 0.9
0.9 - 1.0
1.0 - 1.1
1.1 - 1.2
1.2 - 1.3
1.3 - 1.4
> 1.4
2
3
4
5
6
7
Total


SDGE DS
Actual Events
No
Distributions of Day-of BL Adjustments by Industry Type
SDGE DS Actual Events
Chose Adjustment: No
80%
70%
60%
50%
40%
30%
20%
10%
0%
Percent of Customer-Events
< 0.6
0.6 - 0.7
0.7 - 0.8
0.8 - 0.9
0.9 - 1.0
1.0 - 1.1
1.1 - 1.2
1.2 - 1.3
1.3 - 1.4
> 1.4
Adjustment
2
3
4
5
6
7
Total


SDGE DS
Pseudo Events
No
Distributions of Day-of BL Adjustments by Industry Type
SDGE DS Pseudo Events
Chose Adjustment: No
70%
60%
50%
40%
30%
20%
10%
0%
Percent of Customer-Events
< 0.6
0.6 - 0.7
0.7 - 0.8
0.8 - 0.9
0.9 - 1.0
1.0 - 1.1
1.1 - 1.2
1.2 - 1.3
1.3 - 1.4
> 1.4
Adjustment
2
3
4
5
6
7
Total

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 HVLC Analysis and Definition

This project has produced a wealth of information on the range of load variability of the customers enrolled in CBP and DBP demand response programs, its association with measures of baseline accuracy and potential errors in DR program credits, and the characteristics of customers who are identified as HVLC customers. Examination of the distributions of load variability for those programs, as measured by the average coefficient of variation (CV) of afternoon loads, indicates that the distributions generally turn up sharply (as do measures of baseline errors) after values of approximately 0.2 to 0.3 (*e.g.*, standard deviations around mean values of afternoon load levels of 20 to 30 percent). Two primary conclusions from the analysis of distributions of load variability are the following:

- The CBP programs generally exhibit smaller percentages of customers with relatively high load variability (*e.g.*, 10 to 20 percent of customers have an average CV greater than 20 to 30%) than do DBP programs, for which as many as 30 to 50 percent of customers may exceed that degree of load variability.
- Distributions of load variability also differ substantially by industry type. *Commercial-type* customers (*e.g.*, retail stores, offices, government buildings) generally display the lowest percentages of highly variable loads. The *first and third industry groups* (*i.e.*, agriculture, mining and construction; and wholesale, transportation and other utilities) show the greatest degrees of load variability. *Manufacturing* customers generally include a majority that display relatively low load variability, but also a substantial portion with high load variability. Finally, where present, a large portion of *School* customers have relatively low load factors and high load variability.

In addition, a simulation exercise designed to examine the effect of load variability on potential errors in program credit payments for load reductions demonstrated two primary effects of the structure of CBP and DBP credit mechanisms. First, above a relatively low level of load variability, the potential average percentage payment error is relatively insensitive to the degree of load variability. Second, the payment structure limits the effect of even extremely high load variability on the magnitude of average payment errors.

Given these observations we recommend a relatively conservative HVLC criterion of an average coefficient of variation (CV) for non-event-day afternoon loads in excess of 0.3, or 30 percent. We also provide a straightforward spreadsheet tool that may be used to predict the likelihood that a given customer will exceed the HVLC criterion, using data on readily available customer characteristics data such as industry type, size, and load factor (average demand/ maximum demand). Utility staff may use this tool to screen current and potential future DR program enrollees as part of a process for guiding them to the most appropriate DR program or rate.

Using the recommended HVLC criterion, an average of 25 percent of the program enrollees are identified as HVLC, though results differ substantially by utility and program. In particular, the percentages of HVLC customers are generally lower for CBP than for DBP.

5.2 Analysis of Day-of Baseline Adjustment Factors

Regarding the analysis of baseline adjustment factors for CBP and DSP customers in 2010, the study produced information on the frequency with which the current 20 percent adjustment cap was exceeded, along with more detailed information on the full distributions of baseline adjustment factors by utility and program, for both actual and simulated events, and for customers who selected the adjustment option and those that did not. The following are observations on the ranges of baseline adjustments:

- Adjustment factors of *greater* than the 20 percent cap were substantially more frequent than *downward* adjustments of more than 20 percent (32 percent versus 4 percent overall for actual events, for those selecting the adjustment option).
- Adjustment factors exceeding 20 percent were more frequent for the *actual* events compared to the *simulated* for those customers who selected the adjustment option (32 percent overall compared to 15 percent).
- Adjustment factors exceeding 20 percent were somewhat more frequent for customer accounts *choosing the adjustment option* than for those *not choosing* it (*e.g.*, 32 percent overall compared to 24 percent, for the actual events).