An Uncertainty-Based Analysis on Cost-Effectiveness of Feedback/Behavior-Based Programs within a DSM Portfolio

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ABSTRACT

Feedback/behavior-based programs have been recognized as a mechanism to provide deeper energy savings and higher customer satisfaction. However, due to the limitations of robust ex post program evaluation data, there are significant uncertainties associated with the performance of these emerging programs, particularly, their cost-effectiveness as there is very little program cost data available. This paper presents study results on the impacts and cost-effectiveness of feedback programs within a real DSM portfolio while explicitly considering uncertainties.

Using recent field data and a field-proven DSM analytics tool plus Monte Carlo simulations, the paper first analyzes the potential impacts of five feedback types on increasing a typical DSM portfolio's savings. Second, a detailed cost-effectiveness analysis is conducted using four standard screening tests (TRC, PAC, RIM, and PCT) for two types of feedback programs, Enhanced Billing and Real-Time Feedback. Third, the top three most critical factors impacting cost-effectiveness test results are identified. Finally, a sensitivity analysis is conducted on the factors with highest impacts including annual savings per household, useful life, administrative costs, incentive levels, and avoided costs.

This paper gives program planners and administrators a robust and holistic way to view both potential savings and cost-effectiveness of feedback programs. It supports more informed decisions when integrating this program type into current and emerging DSM portfolios.

Introduction

Program planners and administrators are increasingly challenged to integrate new and cost-effective programs and measures with additional savings potential into their DSM portfolios, especially when faced with state-mandated saving targets under such policies as Energy Efficiency Resource Standard (EERS).

The authors conducted a study referred as "The Big Squeeze" starting in 2010 to help policymakers, program administrators, and other stakeholders understand the challenges this decade holds for continuing the progress of ratepayer-funded energy efficiency programs. The primary objectives of the study were to (1) quantify the savings gap between typical DSM portfolio savings and an average EERS target in 2020, (2) estimate the impacts of recent and new pending federal standards on the savings gap, and (3) assess potential innovative program designs that can narrow the savings gap. (Prindle and Bozorgi, 2011)

We selected a representative energy efficiency program portfolio from a large Eastern-U.S. program administrator to use as a baseline for this analysis. We selected this portfolio in part because it is comprehensive and typical, covering a range of residential and non-residential programs, and in part because the climate is reasonably representative of a national statistical average. This approach allowed us to use actual data; while we have aggregated and masked the data for confidentiality purposes, it makes the analysis reasonably realistic. We then developed several innovative program design scenarios and estimated their potential to increase the portfolio savings and to fill the savings gap between the conventional DSM portfolio and an average nationwide EERS saving target.

In recent years, feedback programs have been recognized as a mechanism to provide deeper energy savings and higher customer satisfaction (Allcott 2012, Ehrhardt-Martinez 2010, Foster 2012, Mazur-Stommen 2013, Zalesny 2012). However, the limited availability of robust ex post program evaluation data creates uncertainties about their performance. To help fill this data gap, we recently conducted a study, using a proven DSM modeling tool plus Monte Carlo simulation techniques to assess the impacts of feedback programs while explicitly considering uncertainties. We used the same prototypical DSM portfolio for baseline purposes, and through a literature review and recent performance data on feedback programs and by using a more robust statistical technique, we quantified how feedback programs could increase the total portfolio savings (Bozorgi and Prindle, 2014). While the original analysis examined a wide range of program types, we focused on feedback programs, because they are both gaining broad interest and have very little measured field data available.

In this study, we 1) refined our initial assumptions (e.g. annual savings and participation) based on the 2013 performance data from multiple feedback programs in the field, 2) conducted a detailed cost-effectiveness analysis on four standard screening tests on two types of feedback programs, Enhanced Billing and Real-Time Feedback, 3) identified the top three most critical factors impacting each of the cost-effectiveness test results, and 4) conducted sensitivity analysis on the factors with highest impacts, which included administrative costs, incentives, useful life, annual savings per household, and avoided costs.

Methodology

Figure 1 shows the three main steps taken to develop the potential savings impacts of feedback programs within the DSM portfolio. Through a review of recent program evaluation data and related literature, we first developed our initial assumptions, such as initial savings, program useful life,program costs or avoided costs. Second, we used the Monte Carlo technique to estimate the probability distributions for each key input parameter, such as electricity savings, participation rate, or useful life. And third, we re-ran the Monte Carlo simulations to generate ranges of impacts on portfolio savings and cost-effectiveness results, and to identify the most critical factors impacting the cost-effectiveness of feedback programs.

The Monte Carlo simulation technique is widely used for modeling uncertainty and risk. It takes input ranges and distributions instead of single point estimates, runs the model repeatedly (e.g. 10,000 times) by randomly drawing values from the specified range of inputs, and generates a distribution of possible outcomes, and estimates of the probability or risk of achieving the expected outcome (the mean of the distribution). This method helps decision-makers understand the probabilities and risks associated with achieving a desired outcome, which helps make more informed decisions.

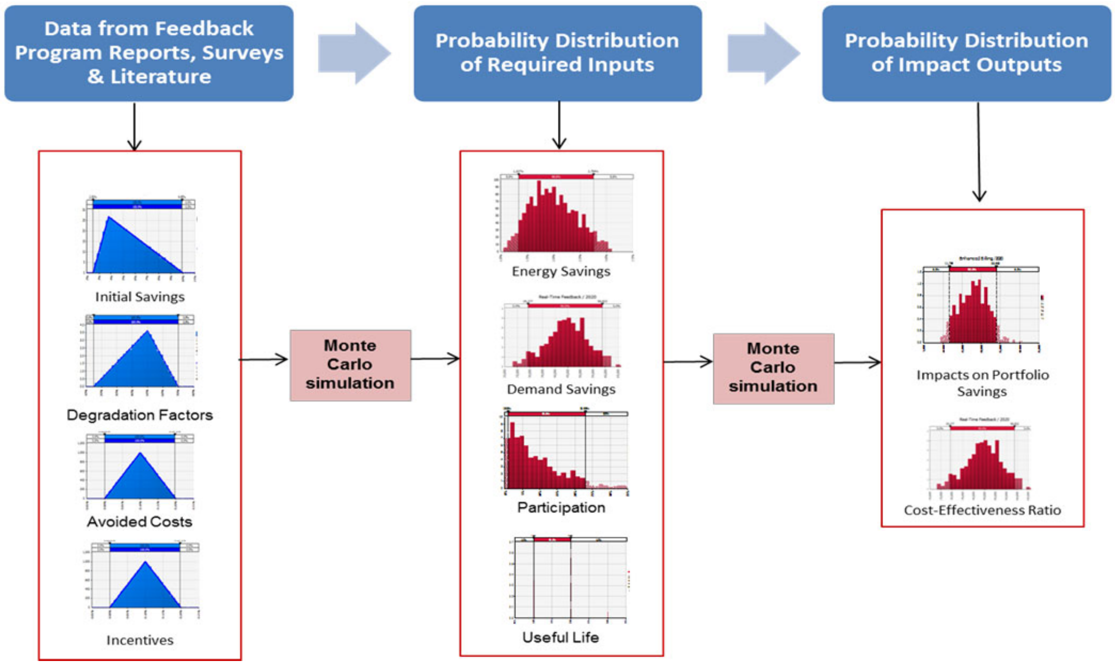


Figure 1. Three-step analytical method (The graph is for the illustrative purpose).

Feedback Program Types

We assessed the savings potential for 5 feedback types: Enhanced Billing, Estimated Feedback, Daily/Weekly Feedback, Real-Time Feedback, And Real-Time Plus Feedback. These program designs fall primarily in the category of feedback programs as defined by ACEEE (Mazur-Stommen 2013). For this analysis, we define the five program scenarios as follows:

1. **Enhanced Billing** - provides detailed information on energy use patterns, often comparing recent to historic consumption or to other households' usage.
2. **Estimated Feedback** – provided mainly via web-based "home energy audit" tools, using statistical techniques to disaggregate total energy usage with little customer-specific data.
3. **Daily/Weekly Feedback**— provided via usage reports that provide specific info and advice on a daily or weekly basis, using average data from other studies
4. **Real-Time Feedback**— which includes in-home energy display devices that provide real time or near real time energy consumption and cost data at the whole-building level.
5. **Real-Time Plus feedback** —most expensive to implement, works with home network and provides real-time energy consumption and cost data disaggregated by appliance.

We assumed that the Enhanced Billing scenario would be an opt-out program, in which customers receive unsolicited feedback (e.g. mailers), but on average realize lower saving percentages per customer. The remaining scenarios are assumed to be opt-in programs, where customers need to take some action to participate. We assigned lower participation rates to the opt-in scenarios, but higher saving rates per customer.

Development of Probability Distributions of Required Input Parameters

This section describes how the key input parameters were developed:

1) Household Electricity Savings

Feedback programs are known to reduce household energy use in at least two ways:

1. Change in Energy-Use Behaviors – direct reduction in energy use
2. Energy Efficiency Investment Behaviors – purchase of high-efficiency technologies

We modeled each of these impacts and aggregated them to calculate total potential savings for the DSM portfolio. Consistent with other program findings (ODC 2012), we estimated that impacts of per-customer behavior change are much greater than those associated with increasing participation rates in existing EE programs. The assumptions and saving calculations are explained in detailed by authors in their paper published at the 2014 AESP conference proceedings. (Bozorgi and Prindle, 2014)

Figure 2 shows annual household savings ranges, resulting from changes in behaviors, at the 90% confidence level. The red probability distribution on the upper left is a sample probability distribution calculated by running some 10,000 iterations. For a better comparison among the feedback types, we transferred the estimated data at the 5%, 50%, and 95% percentiles, from the estimated probability distributions to a bar graph.

The 50th percentile values estimated for each feedback type are consistent with the data found in evaluation reports and other studies (Geller 2012). For example, the average of 1.96% we use for Enhanced Billing is consistent with the 2% average referenced in several studies and the average of 5.36% -7.55% for Real-Time is consistent with the 5-9% range indicated in available studies. It should be noted that because more program evaluation data is available for Enhanced Billing and Real-Time feedback program, the calculated savings for these two programs are better calibrated to the available field data.

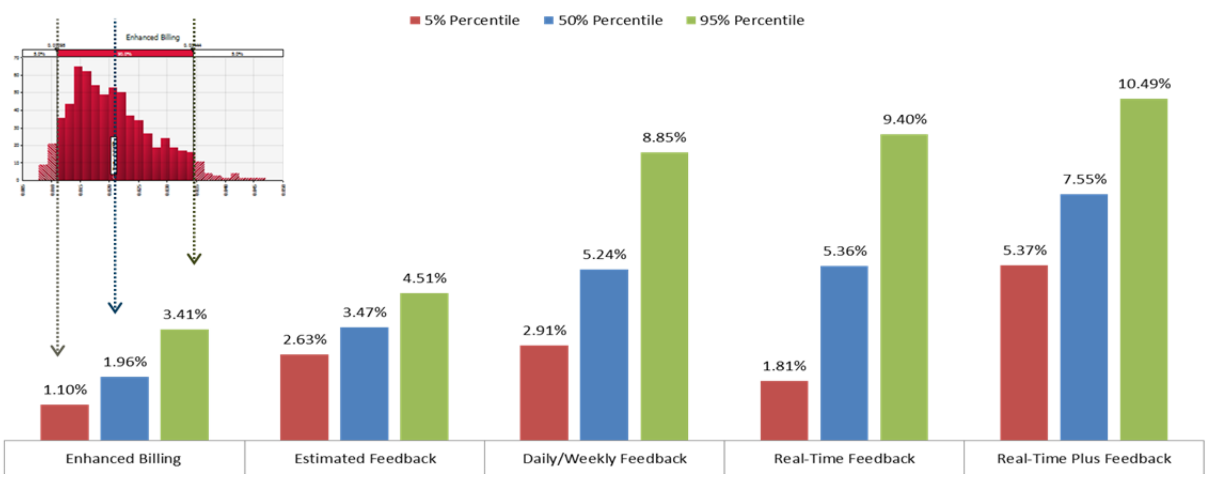


Figure 2. Annual household kWh savings at 90% confidence level (Bozorgi and Prindle, 2014).

2) Feedback Program Participation

In this analysis, participation assumptions for the “Enhanced Billing” scenario were selected based on the data from utilities that run Home Energy Report programs with an opt-out design. We assumed that 10%-25% of total residential customers receive Enhanced Billings (e.g home energy reports by mail) between 2013-2016 and that will expand to 30%-55% between

2017-2020. Participation for the Estimated feedback & Daily/Weekly feedback scenarios are assumed to start at a range of 1-2% with an average of 1.5% and ramp up to 14%-20% with an average of 17% in 2019. For Real-Time feedback types, we assumed participation begins at a range of 1%-3% with an average of 2% and gradually ramps up to a range of 25% - 30% with an average of 27% by 2020. The participation assumptions were primary selected based on ICF experience as well as assumptions found in recent studies in the literature, such as Geller (2012), which draws of much of the other research in projecting program impacts.

3) Feedback Program Useful Life

There are significant uncertainties about the useful lives of feedback programs as it is difficult to determine how long their associated savings will persist, and whether or not the savings will decline or increase over time. For the Enhanced Billing scenario, we assumed that the savings will occur as long as customers will receive reports/mailers. However, based on actual savings observed by such programs, we assumed that the savings for the first year of the program is one third of the subsequent years. Table 1 shows the useful life assumption ranges we use for scenarios 2-5 for this analysis:

Table 1. Range of useful life assumptions

Feedback Program Useful Life	Min	Most Likely	Max
Indirect Programs (except for Enhanced Billing)	1	2	3
Direct Programs	2	5	6
Probability of Occurrence	35%	60%	5%

We assumed a range of 1-3 years with a most likely value of two years for all indirect feedback programs, and a range of 2-6 years with a most likely value of five years for Real-Time feedback programs. We also assigned a probability of occurrence of 35%, 60%, and 5% to minimum, most likely, and maximum case for calculating the distributions. For example, for indirect programs, we assumed that there is a 35% chance that savings will not persist beyond the first year, and that there are 60% and 5% chances that the savings will persist into the second year and third year respectively.

Impact of Feedback Programs on Total Portfolio Savings

Figure 3 shows total estimate impacts of the five feedback programs on total portfolio electricity savings in 2020.

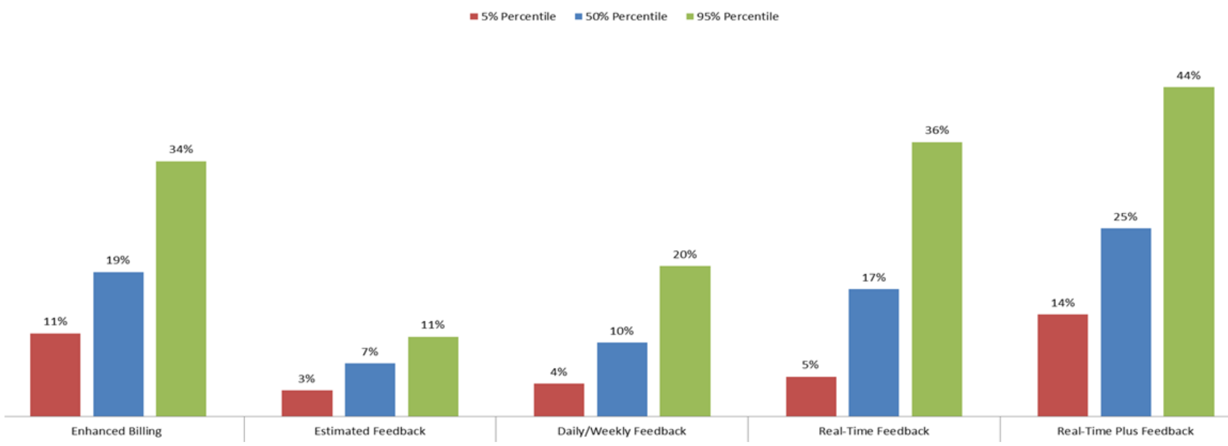


Figure 3: Total impact of feedback programs on portfolio kWh savings.

Cost-Effectiveness Analysis

Cost-effectiveness analysis is conducted on Enhanced Billing and Real-Time Feedback types based on cost data from a few feedback programs implemented in 2013. We looked at four cost-effectiveness screening tests including: Total Resource Cost (TRC), Program Administrator Cost (PAC), Ratepayer Impact Measure (RIM), and Participant Cost Test (PCT).

Table 2 and Table 3 show the ranges of cost assumptions for Enhanced Billing and Real-Time Feedback types: ("Admin Cost – Variable Cost / Participant" is the cost that the program administrator will incur to produce and mail the enhanced bill or energy report)

Table 2. Enhanced billing assumptions

	Min	Most likely	Max
Admin Cost - Fixed (first 4 years for 15-30% participation)	$ 300,000	$ 400,000	$ 550,000
Admin Cost - Fixed (first 4 years for 30-55% participation)	$ 450,000	$ 600,000	$ 850,000
Admin Cost - Variable / Participant	$ 6	$ 10	$ 14

Table 3. Real time feedback

	Min	Most likely	Max
Admin Cost – Fixed	$ 200,000	$ 300,000	$ 500,000
Incentives / Participant	$ 100	$ 200	$ 250
Participant Incremental Cost / Participant	$ 100	$ 170	$ 300

Table 4 shows the ranges of planning assumptions, which were primarily selected based on ICF experience with various programs/utilities across the country. The range of retail rates is selected based on the average of electricity rates in different states.

Table 4. Planning assumptions

	Min	Most Likely	Max
Discount Rate – Company (used for all tests except PCT)	7%	8%	9%
Discount Rate – Participant (used for PCT)	12%	15%	18%

Inflation Rate	1%	2%	3%
2013 Avoided Cost/kWh	$ 0.03	$ 0.06	$ 0.09
2013 Avoided Cost/kW	$ 60	$ 85	$ 110
2013 Retail Rate/kWh	$ 0.08	$ 0.12	$ 0.18

Cost-Effectiveness Results

Table 5 summarizes the results of the life-time cost-effectiveness analysis:

Table 5. Cost-effectiveness results (benefit-cost ratios)

		TRC		
Name	Average	%5 Percentile	%50 Percentile	%95 Percentile
Enhanced Billing	1.38	0.65	1.30	2.59
Real-Time Feedback	1.20	0.22	0.89	2.27
		PAC		
Name	Average	%5 Percentile	%50 Percentile	%95 Percentile
Enhanced Billing	1.38	0.65	1.30	2.59
Real-Time Feedback	1.24	0.23	0.91	2.28
		RIM		
Name	Average	%5 Percentile	%50 Percentile	%95 Percentile
Enhanced Billing	0.38	0.25	0.37	0.55
Real-Time Feedback	0.40	0.16	0.35	0.56
		PCT		
Name	Average	%5 Percentile	%50 Percentile	%95 Percentile
Enhanced Billing	N/A	N/A	N/A	N/A
Real-Time Feedback	2.90	1.20	2.45	4.78

TRC and PAC ratios suggest that both programs can be cost-effective on average. However, their probability distributions of TRC and PAC results, generated from Monte Carlo simulation, indicate that 1) there is a higher chance (about 59%) that the Real-Time Feedback program show TRC and PAC results smaller than one and thus would not be cost-effective, and 2) there is a smaller chance (about 29%) that the Enhanced Billing program does not pass the TRC or PAC tests. Figure 4 and Figure 5 show the distribution of TRC results for Real-Time Feedback and Enhanced Billing scenarios. Thus, with current assumptions, the Enhanced Billing scenario is more cost-effective compared to Real-Time Feedback type.

Both programs resulted in very low RIM results with about a 90% chance of benefit-cost ratios smaller than 0.5. PCT is not applicable to the Enhanced Billing program as participants do not incur any costs for receiving their enhanced bills or energy reports.

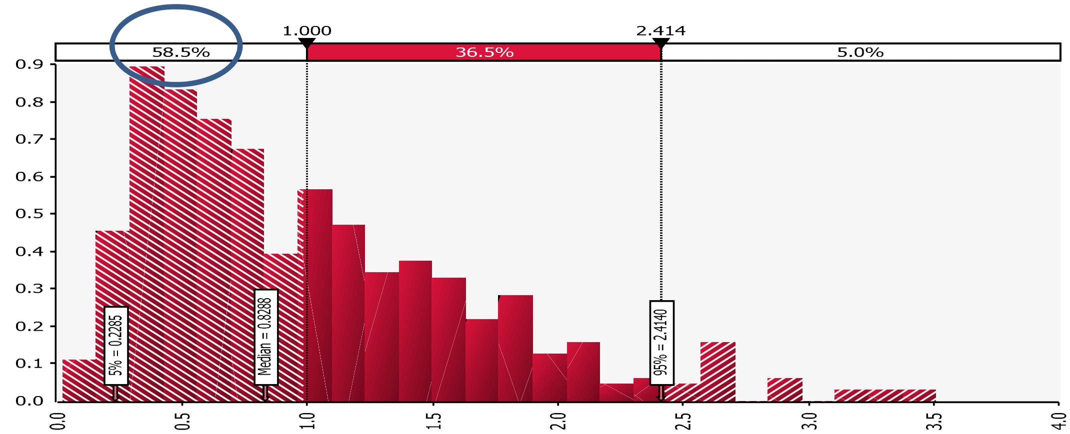


Figure 4. Distribution of TRC ratio for real-time feedback.

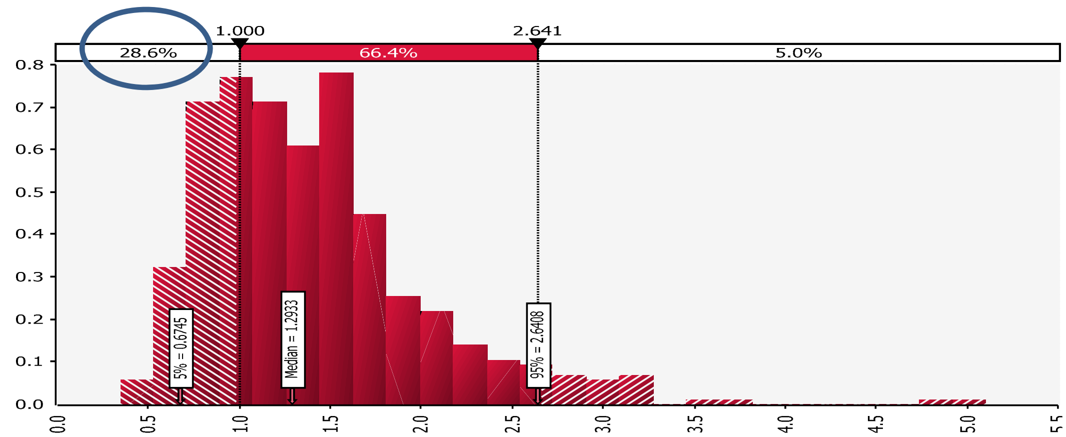


Figure 5. Distribution of TRC ratio for enhanced billing.

Top Three Critical Factors Impacting Cost-Effectiveness

The tornado graph in Figure 6, generated through Monte Carlo simulation, shows correlation coefficient for all factors impacting the TRC calculation for the Enhanced Billing scenario and ranks the factors based on their level of impact, both positive and negative. Through this kind of analysis, we identified the top three factors with highest impact on each cost-effectiveness ratio for each program. Top three factors for each program and cost-effectiveness ratios are summarized in Table 6:

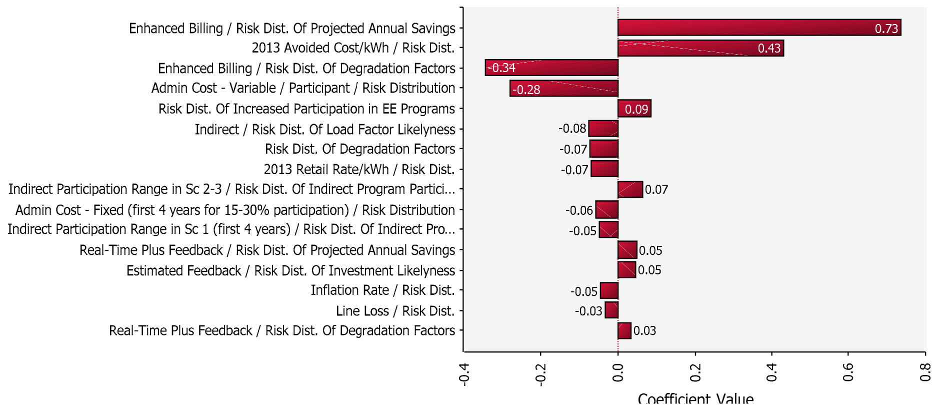


Figure 6. Correlation coefficients for enhanced billing – TRC calculation.

Table 6. Three most critical factors impacting cost-effectiveness of feedback programs

	TRC		PAC		RIM		PCT
	Enhanced Billing	**Real-Time Feedback**	**Enhanced Billing**	**Real-Time Feedback**	**Enhanced Billing**	**Real-Time Feedback**	**Real-Time Feedback**
Highest	Household Savings	Household Savings	Household Savings	Household Savings	Avoided Cost/kWh	Household Savings	Household Savings
2nd Highest	Avoided Cost/kWh	Useful Life	Avoided Cost/kWh	Useful Life	Retail Rate/kWh	Useful Life	Useful Life
3rd Highest	Admin Cost - Variable	Participant Cost	Admin Cost - Variable	Incentives	Household Savings	Avoided Cost/kWh	Participant Cost

- Annual Electricity Savings per Household has the highest impact across all cost-effectiveness tests, expect for the RIM test for the Real-Time Feedback program for which it has the third highest impact.
- Useful Life has second highest impact for the Real-Time Feedback program in all tests, followed by Participant Incremental Cost, Incentives, and Avoided Cost/kWh.
- Avoided Cost/kWh is the second most critical factor for TRC and PAC tests for the Enhanced Billing program, followed by Admin Cost – Variable per Participant.
- Retail Rates/kWh is among the top three factors only for the RIM test for the Enhanced Billing program.

Sensitivity Analysis on Cost-Effectiveness

We conducted sensitivity analysis on the most critical factors identified in Table 6, which include Annual Savings per Household, Program Costs, Useful Life, and Avoided Costs/kWh. We used the parameters/assumptions previously presented in the paper as the base case, and developed two additional scenarios, Low and High, for each of most critical factors. Note that since all of the analyses in this paper are conducted through Monte Carlo simulation, we have selected Min, Most Likely, and Max assumptions for both Low and High scenarios.

Annual Savings per Household

Table 7 shows the assumptions, we developed for each scenario by reducing and increasing the base case annual savings by 30%, and Figure 7 shows the results graphically.

Table 7. Sensitivity analysis assumptions - annual savings per household

	Low Saving - 30% Reduction			**Base Case**			**High Saving - 30% Increase**		
	Min	**Most likely**	**Max**	**Min**	**Most likely**	**Max**	**Min**	**Most likely**	**Max**
Enhanced Billing									
Annual Savings	0.76%	**1.38%**	2.37%	1.10%	**1.96%**	3.37%	1.44%	**2.50%**	4.38%
Real-Time Feedback									
Annual Savings	1.29%	**3.77%**	6.51%	1.79%	**5.38%**	9.52%	2.26%	**6.88%**	12.09%

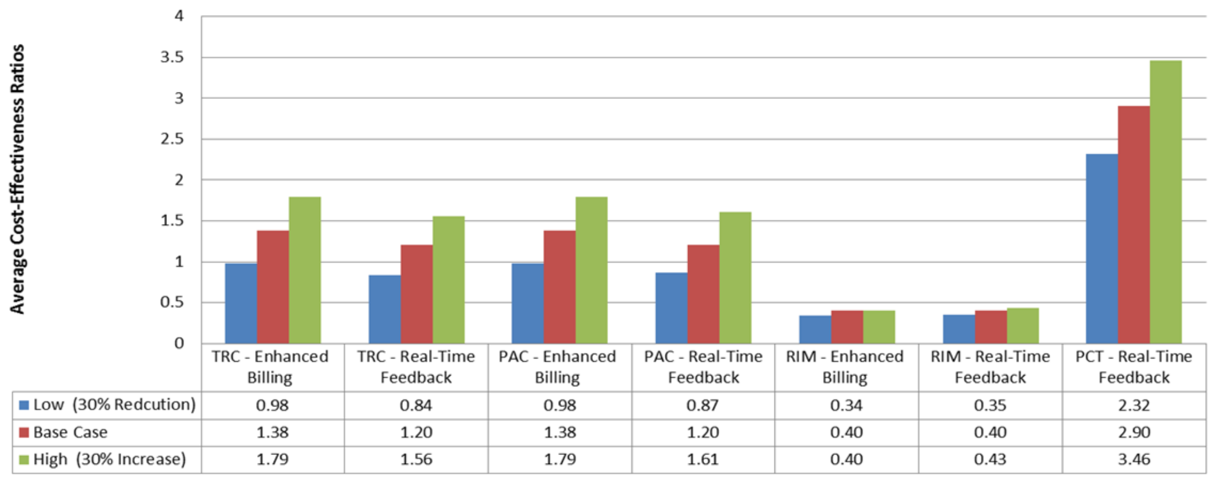


Figure 7. Sensitivity analysis results – Annual savings per household.

Program Costs

Table 8 shows the assumptions we developed for each scenario by reducing and increasing the base case program costs by 30%, and Figure 8 shows the results graphically.

Table 8. Three most critical factors impacting cost-effectiveness of feedback programs

	Low Cost - 30% Reduction			**Base Case**			**High Cost - 30% Increase**		
	Min	**Most likely**	Max	Min	**Most likely**	Max	Min	**Most likely**	Max
Enhanced Billing									
Admin Cost - Variable	$4	**$7**	$10	$6	**$10**	$14	$8	**$13**	$18
Real-Time Feedback									
Participant Cost	$70	**$119**	$210	$100	**$170**	$300	$130	**$221**	$390
Incentives	$70	**$140**	$175	$100	**$200**	$250	$130	**$260**	$325

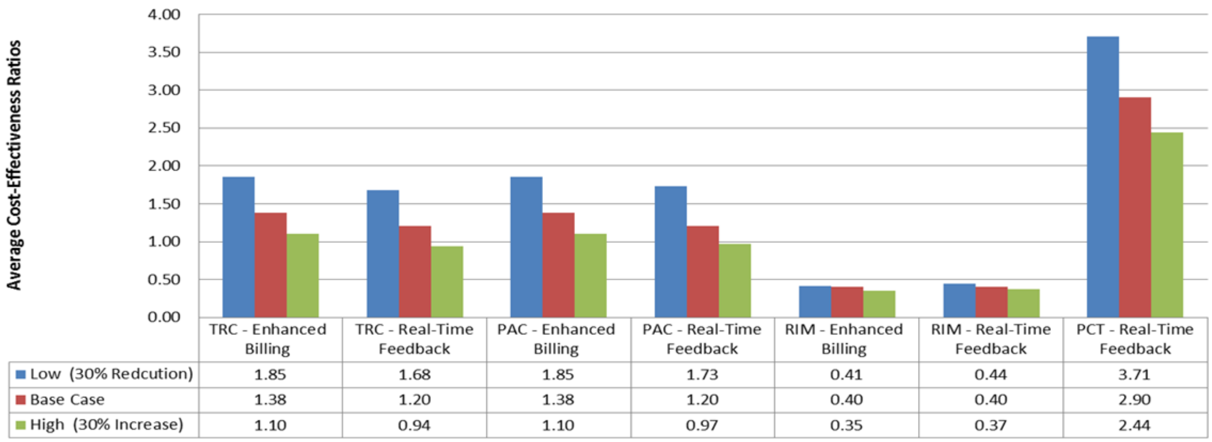


Figure 8. Sensitivity analysis results– program costs.

Useful Life

Table 9 shows the assumptions for useful life of the Real-Time Feedback program, and Figure 9 shows the results graphically.

Table 9. Sensitivity analysis assumptions - Useful life for real-time feedback

	Low - Useful Life			Base Case			High - Useful Life		
	Min	**Most likely**	Max	Min	**Most likely**	Max	Min	**Most likely**	Max
Useful Life	1	**3**	4	2	**5**	6	3	**7**	10

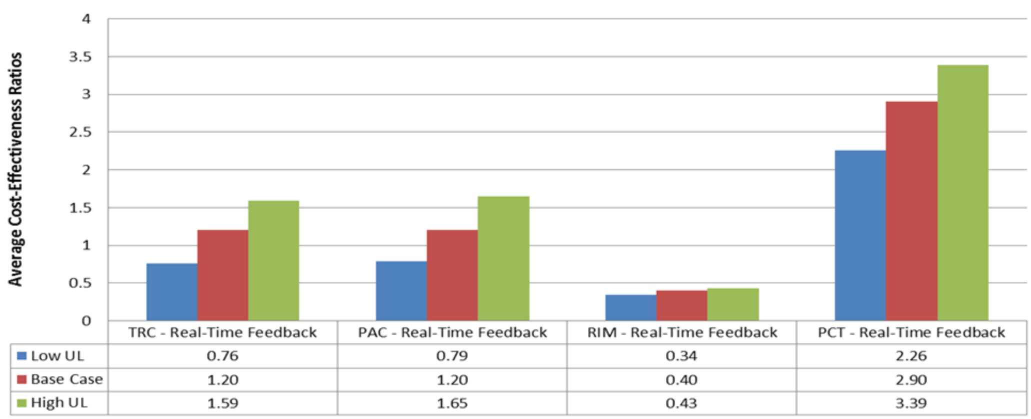


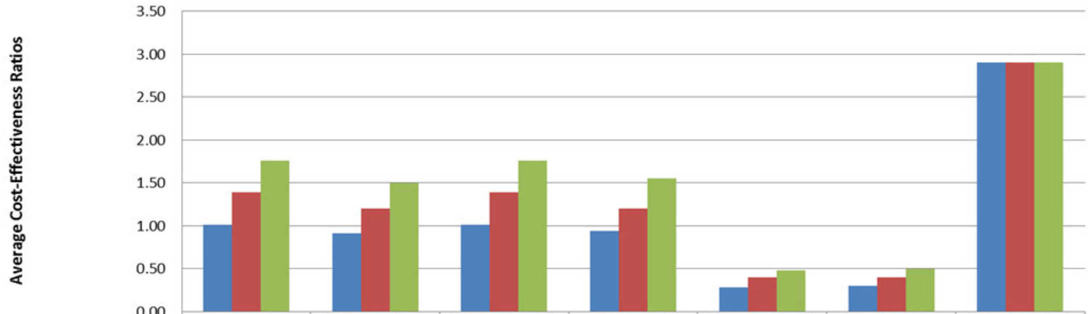
Figure 9. Sensitivity analysis results – Useful life for real-time feedback.

Avoided Costs/kWh

Table 10 shows the assumptions we developed for each scenario by reducing and increasing the base case avoided costs by 30%, and Figure 10 shows the results graphically.

Table 10. Sensitivity analysis assumptions – avoided costs

	Low - 30% Reduction			Base Case			High - 30% Increase		
	Min	**Most likely**	Max	Min	**Most likely**	Max	Min	**Most likely**	Max
Avoided Costs	$0.02	**$0.04**	$0.06	$0.03	**$0.06**	$0.09	$0.04	**$0.08**	$0.12



	TRC - Enhanced Billing	TRC - Real-Time Feedback	PAC - Enhanced Billing	PAC - Real-Time Feedback	RIM - Enhanced Billing	RIM - Real-Time Feedback	PCT - Real-Time Feedback
Low (30% Redcution)	1.01	0.91	1.01	0.94	0.28	0.30	2.90
Base Case	1.38	1.20	1.38	1.20	0.40	0.40	2.90
High (30% Increase)	1.76	1.49	1.76	1.55	0.48	0.50	2.90

Figure 10. Sensitivity analysis results – Avoided costs.

Conclusions

In our core analysis, TRC and PAC results suggest that both Enhanced Billing and Real-Time Feedback programs can be cost-effective on average. However, 1) there is a higher chance (about 59%) that the Real-Time Feedback program will show TRC and PAC benefit-cost ratios smaller than one and would thus not be cost-effective, and 2) there is a lower chance (about 29%) that the Enhance Billing program will not pass the TRC or PAC tests. Both programs resulted in very low RIM results with about 90% chance of being smaller than 0.5.

In our sensitivity analysis, annual savings per household shows the highest impact in TRC, PAC and PCT tests. Useful Life has second highest impact for the Real-Time Feedback program in all four tests, followed by participant cost and incentives. Avoided cost/kWh is the second most critical factor for TRC and PAC tests for the Enhanced Billing program, followed by admin cost – variable per participant (costs of generating reports, mails, etc.). Program planners and administrators may not have much control over avoided costs or retail rates, but they should continuously consider innovative methods to deepen customer behavior impacts to achieve higher, more consistent energy savings, while reducing their program costs.

It should be noted that the results of this study may not be directly applicable for designing and/or delivering feedback programs for a particular state or utility service area, as we did not consider key demographic or geographic factors such as customer propensity to participate, customer load shape characteristics, potential benefits of a given behavioral incentive design, or availability of smart metering infrastructure to enable and support various program designs. Nonetheless, we believe the methods and the results are encouraging and that DSM planners should explore these options. By quantifying the range of possible outcomes and the associated uncertainty and risk, this analytical approach gives DSM planners and administrators a more rigorous way to consider feedback programs.

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