Reducing the Risks:
Key Parameters When Planning Cost Effective DSM Programs

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ABSTRACT

Planning for DSM/DR/EE programs must be done in a way that is comparable to supply side options to assure equity and to make sound decisions on what is cost effective. There are many assumptions that go into DSM/DR planning as well as supply side planning. These assumptions cover a wide range of categories including technologies to consider, program delivery assumptions, implementation rates, free rider expectations and incentives, among others. However there are many "non-program" factors that should be considered when determining cost effectiveness of the programs, as well. These include financial assumptions such as real discount rates and tax rates as well as customer rates, T&D costs and environmental costs, among others. In addition there are future price expectations, current market prices, market penetration potentials, adoption rates and a host of other important assumptions. The objective of this paper is to explore which of these many factors are key parameters that affect cost effectiveness when completing program, design and implementation planning. In addition the paper will help the audience to understand which assumptions have the biggest impact on the analysis and where to focus resources to refine the assumptions.

Introduction

When planning Demand Side Management, Demand Response or Energy Efficiency (EE) programs there are many inputs into a model to determine cost effectiveness. These inputs are critical to avoid "garbage in: garbage out" results in the model. They also must be consistent with corporate model assumptions so that EE is comparable to supply side options. Some of these assumptions are easy to calculate based on sound engineering analysis of a technology such as lighting wattage differences. Others are estimates that vary or are constantly changing such as local, regional and national market trends and interest rates. Still others are hard to accurately measure as they deal with markets and consumer attitudes such as free riders. So the question is with all these variables, which have the largest impacts or risks on the cost effectiveness results for which planner must either refine the data or run various sensitivity analyses. For example as a planner doing an EE program how much impact does the assumption of free riders have on my results? Are my programs cost effective with little margin for error on this assumption thus I should spend more time and effort to nail down the free rider assumption? This paper shares the results of testing variables in three main areas in the cost effectiveness analysis, 1) Market-based uncertainty including price (avoided cost) assumptions and weather related variation in savings 2) Financial uncertainty including cost-of-capital, utility rates, losses, and forward escalation assumptions, and 3) the program implementation and operation uncertainty. To provide guidance on which of these are the more critical assumptions and suggest methods to assess the risk around those numbers, four typical incentive measures were modeled including Residential CFLs, Commercial CFLs, High Bay Florescent Lighting 6LF32T8, and Commercial Rooftop Cooling Units.

Methodology

To complete this analysis we used several standard program technologies as a base and adjusted many different variables to assess the results. To do the analysis we relied on two tools – DSMore and Crystal Ball. The contribution of each to this paper is described below.

DSMore

To determine cost effectiveness we used the DSMore model[1] which was created by Integral Analytics for the primary purpose of evaluating the value and cost effectiveness of energy efficiency and demand response programs under both cost based and market-based avoided cost electricity contexts. It is based on several underlying statistical models that work together to provide probabilistic assessments and forecasts of current and future avoided cost conditions within electric markets. [2] From a program perspective DSMore allows the planner to put in many different incentives, participation, costs and other variables from which to plan and analyze the program. An additional benefit is that DSMore runs quickly, and directly in conjunction with either Crystal Ball or @Risk, so that numerous iterations can be computed quickly where Crystal Ball operates directly on the DSMore calculation engine to join the two sets of tools together into single analysis.

Crystal Ball

To automate "what if" analysis around the key program drives with Monte Carlo simulation we used the Crystal Ball software tool. The program provides for a range of values to inputs parameters and automatically calculates thousands of different outputs and their probabilities. These results are reported as probability distributions and used for in-depth analysis. We use the results to explore which parameters are most important for program success. In essence, DSMore is the modeling tool framework on which Crystal Ball operates, in this case.

Variables for Analysis

Several key variables are analyzed in this paper to try to understand the significance of each. In

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1 Winner of AESP 2007 Innovative Product Award

2 DSMore starts with a *Causal Simulation* methodology that models hourly customer loads using optimally-selected, historical non-linear regression equations, for each month and day type, which uniquely (per hour) relate load savings to temperature, humidity, year, wind speed, interaction effects and other potential factors. Optimally selected weather response functions are used to simulate the customer's usage and DSM load savings over 30+ years of possible weather scenarios.

A range of possible forward market prices are then combined with the weather uncertainty to arrive at a joint set of distributions for future loads and prices. The hourly forward market price forecasts are based upon sophisticated, and widely used, weather based conditional GARCH models[2]. GARCH models are widely used within the energy planning community to best express and value the daily and hourly expectations of forward energy costs, and hence potentially avoided costs for demand side measures.

The GARCH based price forecasts are also simulated through the same hourly weather patterns as are used for the load savings forecasts, insuring that an hour by hour alignment of prices and loads is established, leading to the most accurate and comprehensive valuation of demand side resources possible. This process insures that the hourly covariance's between prices and loads is measured, which insures that the most appropriate valuation of demand side resources is achieved and comparable comparison with the supply side, or market based options. By correlating expected future prices and forecasted future load savings through the same set of hourly weather observations, DSMore insures that extreme weather conditions, which will lead to high demand, will also be valued under commensurately high market prices, as we would expect.

general, we categorize the uncertainties into three main areas for the cost effectiveness analysis: 1) price (avoided cost), weather assumptions, and market based assumptions (market uncertainty), 2) financial assumptions (financial uncertainty), and 3) program implementation, operation and participation assumptions (program uncertainty). Only the program uncertainties are able to be influenced by the program designers. Market & Financial uncertainties depend on prices, supply and demand imbalance, and weather conditions.

Although market and financial uncertainty are only indirectly influenced by program design, these are included in the paper to demonstrate that much of the uncertainty around cost effectiveness is a function of unpredictable future conditions. With that said, the real focus of this paper is in those uncertainties that a program designer is able to influence or should understand as he/she designs program options. The parameters considered include the following:

Market Uncertainty

- Weather –The variable of high and low temperatures around the average over time
- Market Energy Prices/Cost – The cost of energy traded in the market.
- Capacity Price – The price of new capacity.

Financial Uncertainty

- GHG Emission Cost – Green House Gas costs assessed or traded.
- Inflation (Escalators) – Inflation or escalation of various costs over time.
- Discount Rate – The cost of money over time.
- Utility Rates – The rates that the customer sees from a specific utility
- Ancillary Services Rates – Extra costs of service or of trading transactions.
- Electric Losses – System losses from generation to the customer

Program Uncertainty

- Measure Life – Effective Useful Life (EUL) of the efficiency measure installed
- Incentives – Incentives to the customer or market actors to encourage adoption
- Participation – Number of participants assumed to be included within the program and getting savings
- Savings – kWh, kW or therm savings over a baseline
- Administrative Costs – Costs to administer, market and implement a program
- Free Riders/Spillover – Net of customers who would have implemented the measure anyway minus the customers who participated due to the program but did not get tracked.

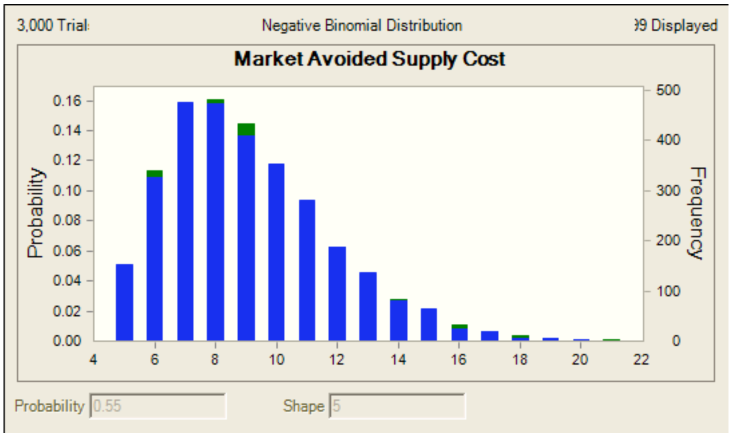
Each uncertain assumption is characterized by a probability distribution describing the full range of uncertainty facing the program designer. These distributions are then used by Crystal Ball in a Monte Carlo analysis of the total program cost effectiveness. The ranges of change within these uncertainty variables were established from past program design experience as shown in the following table:

	Distribution Type	Range	Standard Deviation	Average	Applied to
Market Uncertainty					
• Weather	Normal		15%	100%	Targeted Savings
• Market Energy Prices/Cost	Negative Binomial	Prob 0.55 and Shape 5			Avoided Costs Scenario
• Capacity Price	Normal		\$7.00	\$70.00	
System/Financial Uncertainty					
• GHG Emission Cost	Triangular	\$15-25/Ton CO2		\$20/Ton CO2	
• Inflation (Escalators)	Triangular	1-4%		2.50%	
• Discount Rate	Normal		1.67%	7%	
• Utility Rates	Triangular	90-130%		100%	Rates
• Ancillary Services Rates	Normal		7%	100%	Rates
• Electric Losses	Triangular	5-15%		10%	
Program Planning Uncertainty					
• Measure Life	Custom	Measure Dependent			
• Incentives	Uniform	10-120%			
• Participation	Triangular	70-200%		100%	Participation
• Savings	Normal		10%	100%	Targeted Savings
• Administrative Costs	Triangular	50-200%		100%	Costs
• Free Riders	Triangular	10-25%		15%	

To understand how these uncertainties might impact different types of programs four typical incentive measures were modeled, Residential CFLs, Commercial CFLs, High Bay Florescent Lighting 6LF32T8, and Commercial Rooftop Cooling Units. Given four program measures with 15 different uncertainty parameters across multiple ranges, there were many thousands of permutations from which to analyze the impact of system or program changes. Using Crystal Ball, these uncertainties are characterized by probability distributions. For example, a few of the key uncertainties are shown below.

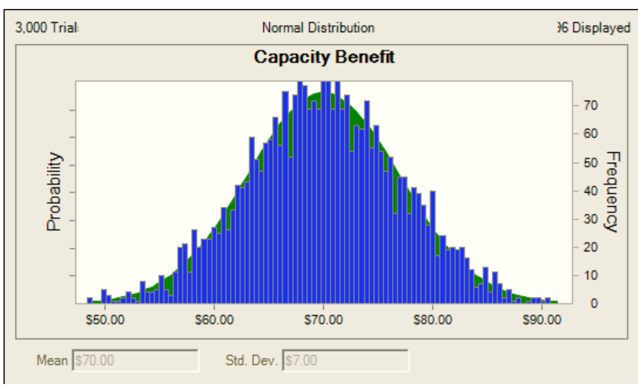
Market prices are represented by a lognormal distribution. As noted above, DSMore represents future avoided costs, or prices, based on historic forward price variation. The distribution used for this study references the DSMore price distribution. Both the Crystal Ball price scenario distribution and the corresponding market price are shown below. Crystal Ball selects scenarios 1 though 21. If scenario 12 is selected for example, the corresponding DSMore market price is \$51.26/kWh representing the average annual around the clock price of market energy.

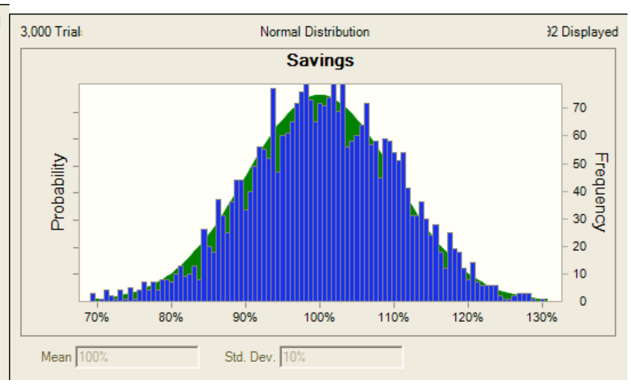
Average Annual ATC Price



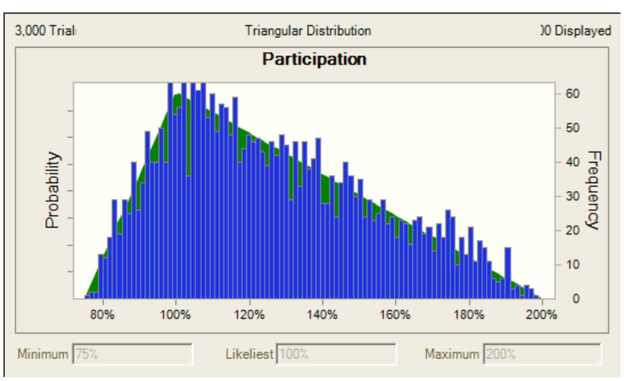
Scenario	$ / MWh
1	$37.48
2	$30.51
3	$32.35
4	$34.31
5	$36.03
6	$38.02
7	$39.29
8	$41.65
9	$43.89
10	$46.47
11	$48.24
12	$51.26
13	$53.13
14	$55.01
15	$56.95
16	$58.83
17	$60.71
18	$64.53
19	$69.03
20	$74.40
21	$75.88

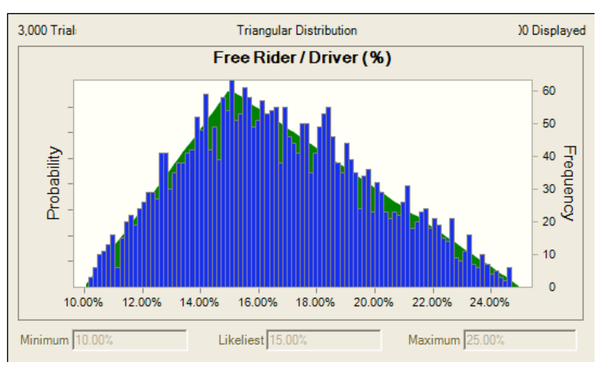
Several assumptions are represented as normal curves. For example Capacity Benefit shown below is represented as a normal curve with an average of $70/kW with extremes of from $50/kW to $90/kW. Other assumptions are represented as a percentage away from the expected value. Savings for example is shown below represented in this way.



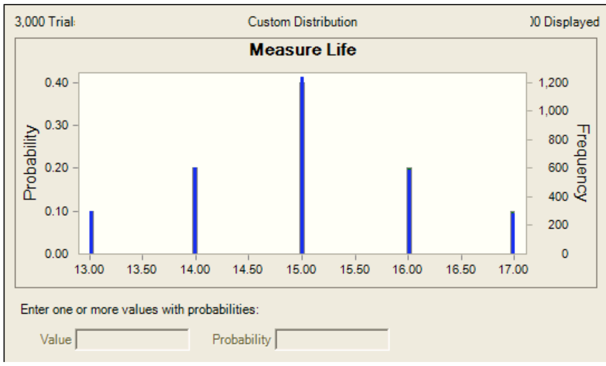


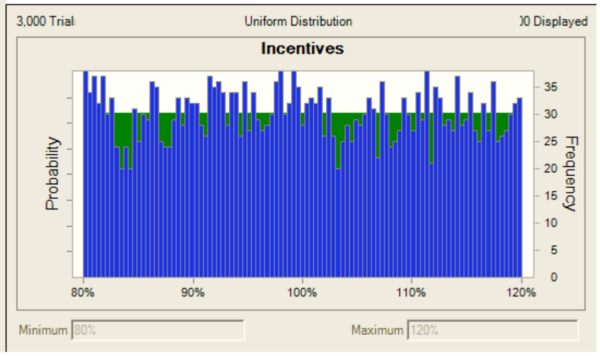
Other assumptions are represented a triangular distributions. Participation and Free Riders are represented in this way as shown below.





Measure life is represent as a discrete triangular distribution as shown below in the case of Commercial High Bay Fluorescent bulbs. Incentives are represented as a uniform distribution. Represented in this way, several choices of incentives are equally simulated without favoring one value over another.





Results

Market Uncertainty

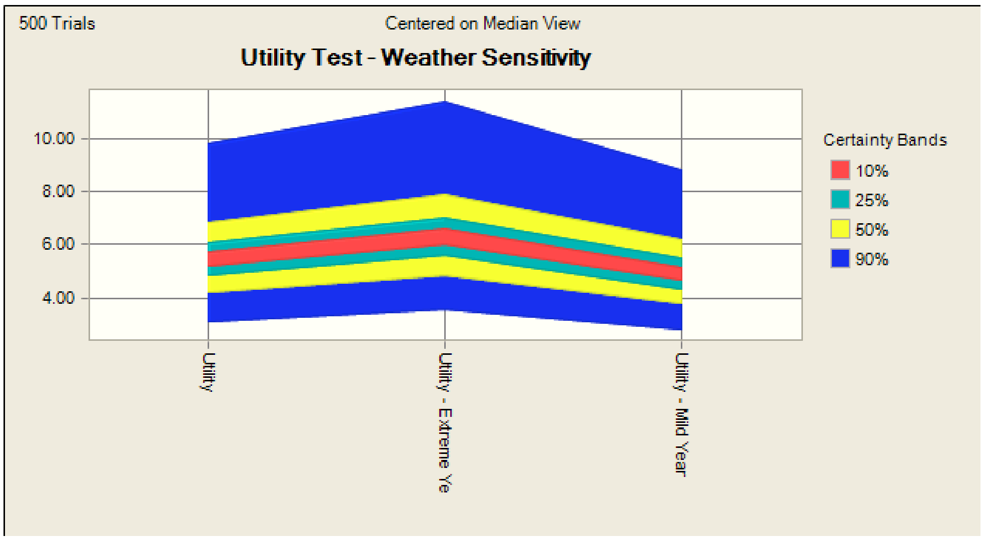
When examining market uncertainty using DSMore, we are able to measure market price risk and weather related risk together. This is important because the correlation between the two is tight. High temperatures create higher demand and thus higher prices. As expected for some programs, market related price risk is a significant source of uncertainty affecting program cost effectiveness. In the example below for the AC program, nine unique values are reported for both the Utility Cost Test (UCT) and the Total Resource Cost (TRC) Test[3]. This shows how EE measures that save during a significant extreme weather, high market price event are almost five times more valuable from a cost effectiveness standpoint as the low prices in a mild year. Consequently utilizing "average" weather will undervalue EE programs value and not provide its true cost effectiveness versus supply side options. The comparable analogy on the supply side is often referred to as the reserve margin. If there were no asymmetric financial loss or risk associated with extreme weather, supply side planners would not need to plan for a reserve margin. As such, it is important to measure and value this asymmetry, which can only be done using hourly level models, such as DSMore or supply side production cost models.

Market Price/Weather Scenarios					
		Cost	Market Price Index Based		
Usage/Weather Scenarios	Test	Based	Low	Median	High
Mild Year	Utility	4.63	2.94	4.76	7.71
Normal Year	Utility	5.43	3.28	5.89	9.34
Extreme Year	Utility	6.43	3.76	7.26	10.87
Mild Year	TRC	2.35	1.49	2.41	3.90
Normal Year	TRC	2.75	1.66	2.98	4.73
Extreme Year	TRC	3.26	1.90	3.68	5.51

The chart below further highlights the contribution of weather to program uncertainty. The chart shows the expected and extreme outcomes of the Utility Cost Test ratios for three weather sensitivity studies – expected, extreme weather, and mild weather. In the case of a mild year, for example, the overall benefits decrease, but the distribution or uncertainty around the expected results also

[3] For full definitions of the cost benefit tests see the California Standard Practice Manual: Economic Analysis Of Demand-Side Programs And Projects , Oct 2001

significantly decreases. The opposite is true of the extreme weather year, the expected benefit increases and the overall uncertainty surrounding the program increases. Unlike the table shown above, the chart considers only the cost-based results. Clearly from these results we can conclude that weather related uncertainty can cause extreme variation in the final program cost-effectiveness outcome. The program may be highly cost effective or may even fail cost effectiveness under certain weather conditions. Unfortunately for the planner, there is nothing that can be done to influence weather outcomes. However, it is possible to build into the program some contingencies to account for extreme weather conditions. At a minimum a program planner can report the possible variation that is expected from weather related uncertainty.

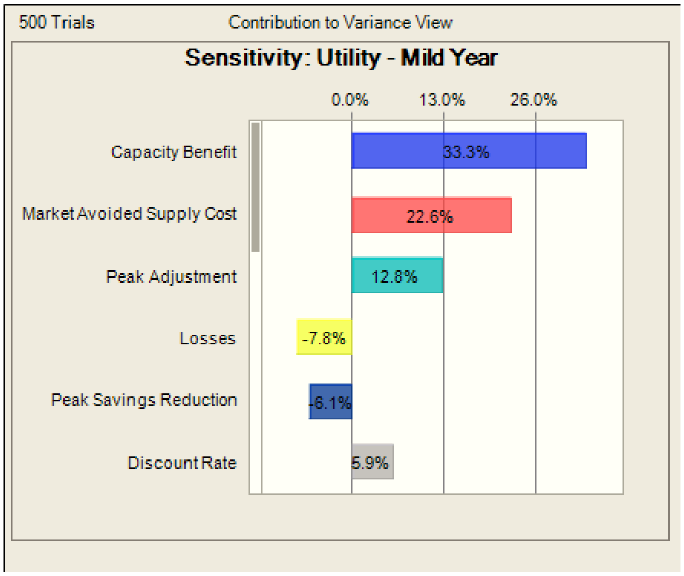


Crystal Ball is able to report sensitivity charts displaying the contribution of each uncertain assumption cell to the overall variance in the test results. Both the relative importance of the variable and the direction of influence are shown. A large positive variable would indicate that attention given to increasing that variable would yield the most effective positive influence on the cost effectiveness results. Likewise, effort should be given to reducing large negative variables.

The sensitivity chart for the High Bay Fluorescent 6LF32T8 is shown below. In this chart we see the contribution of prices on the overall test result. Capacity prices and energy prices (shown as Market Avoided Supply Cost below) contribute most to overall cost effectiveness variance. This is a logical conclusion given that the efficiency benefits occur to avoid capacity and market supply purchases. Together, capacity and energy prices contribute over 55% of the overall uncertainty for this measure. It is interesting to note that this is true even though savings from high bay fluorescent lighting is not directly affected by weather, but only indirectly due to the weather related volatility in energy prices.

The uncertainty in capacity prices on the other hand are more affected by the long-term displacement of generation resources. Capacity prices are often modeled as a single avoided capacity benefit such as an avoided peaking unit. However, a more accurate approach would consider the amount of capacity and the total hours the efficiency measure is displacing annually and align the measure with an equivalent supply side resource in the supply stack. In the case of high bay fluorescent lighting, the measure would certainly displace base load or mid-merit capacity as the lighting measure potentially contributes benefits during all hours of the year. In this study, the capacity benefit was limited to a range of between $50.kW and $90/kW with an average of $70/kW.

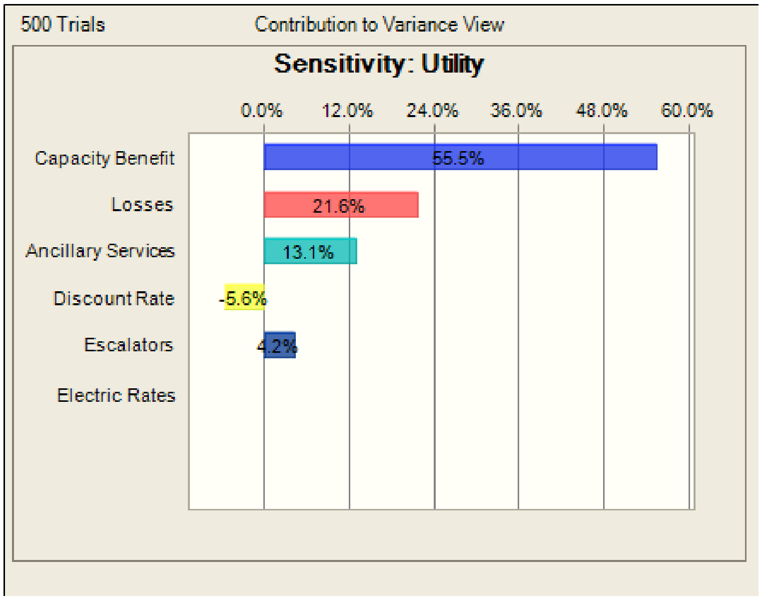
High Bay Fluorescent 6LF32T8



Financial Uncertainty

The second category of uncertainty examined in this study is financial related. Like Market Uncertainty previously discussed, the types of uncertainty in this section are still not be directly influenced by the program design choices of the program planner. However, the range of uncertainty surrounding the variable can greatly impact the eventual cost effectiveness analysis of the measure. The impact of avoided capacity and avoided market energy benefits are removed from these charts. When looking at cost benefit analysis losses and any ancillary services are significantly more important than things such as discount rates, your customer electric rates (not market prices), and escalators. That is because your efficiency benefits are driven by the first three assumptions. As a planner you should work with the utility forecasting team to get their assumptions for these key parameters to make sure there are consistencies as well as reasonableness in the assumptions. Doing so will help make sure the result is one more accurate but second these results will then be comparable to the other utility forecasting models.

High Bay Fluorescent 6LF32T8



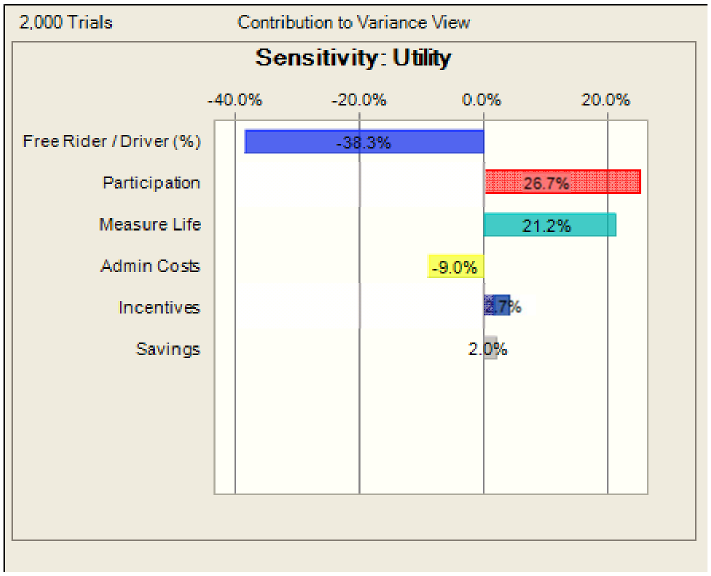
Program Uncertainty

The third category of uncertainty, Program Uncertainty, is examined in this section. Program uncertainty considers those parameters most influenced by program design. The results indicate that the key parameters differ depending on which cost effectiveness test you are most concerned with, the type of measure the program is focusing on, and the customer class and load shape targeted. The first chart below considers a commercial AC measure. We show the sensitivity results for the Utility Cost Test (UCT).

When looking from the Utility Cost Test perspective you look at the benefits and costs from the utility's perspective only. Here Free Rider/Driver and incentive levels become more significant. On administrative costs the significance becomes more important depending on how the program is set up. Are there high fixed costs for the program in marketing, assessment or tracking costs or are administrative costs variable with participation for things such as incentive processing? When there are more fixed costs then the participation becomes more important.

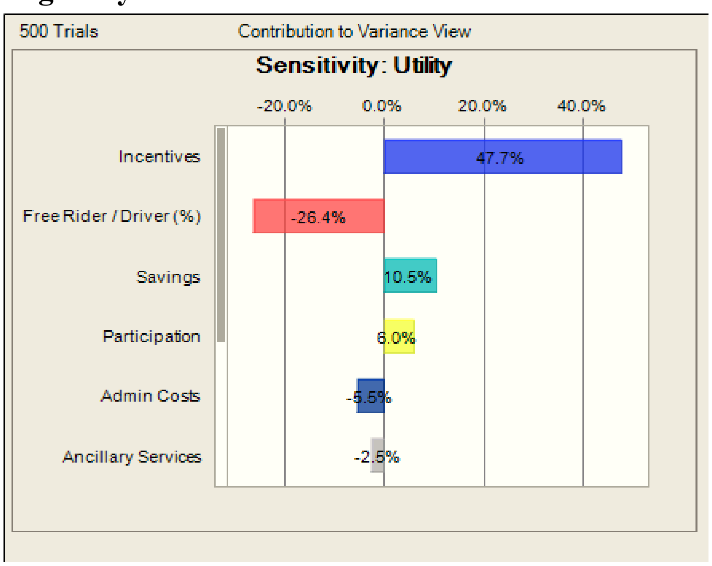
The costs for the Utility Cost Test are the program costs incurred by the administrator, the incentives paid to the customers, and the increased supply costs for the periods in which load is increased. Administrator program costs include initial and annual costs, such as the cost of utility equipment, operation and maintenance, installation, program administration, and customer dropout and removal of equipment (less salvage value) for a load control program, or incentives, marketing, technical support and processing in an prescriptive measure program. In this test, revenue changes are not relevant. Though a shift in revenue affects rates, a test result above 1.0 informs us that the DSM program will yield long run rates that will not rise as quickly as if we had opted for the supply side alternative. Where supply is low, or demand is rising quickly, distribution systems are constrained and supply is required, rates are likely to rise. The Utility Cost Test results in a measure of which option, DSM or supply, is likely to be the least cost option.

AC 135,000 - 240,000



The following chart focuses on a commercial fluorescent measure. In the chart we show the sensitivity of various program parameters on the Utility Cost Test ratio. For this measure, the incentives contribute the majority of uncertainty in test results. The free rider assumptions are next followed by the savings assumptions

High Bay Fluorescent 6LF32T8

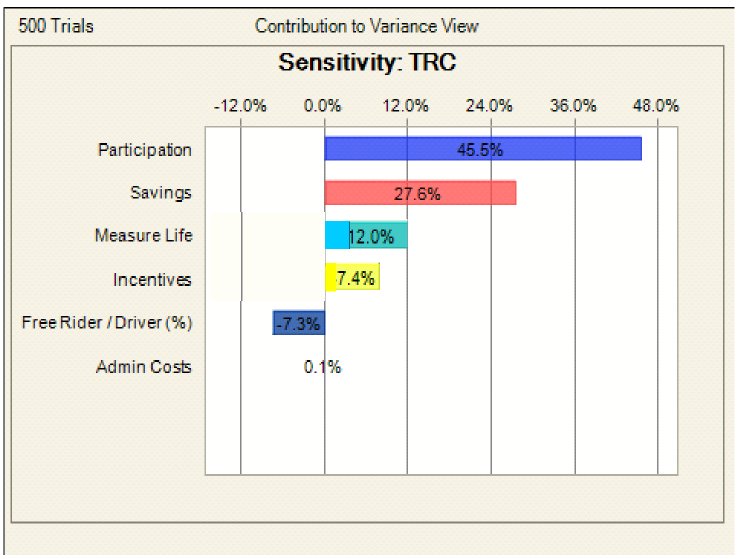


In the chart below we show the sensitivity results for a residential lighting measure. In this chart we focus on the Total Resource Cost Test results. The TRC Test measures the net costs of a DSM program from the combined point of view of both the participants' and the utility's costs. In a sense, it is the summation of the benefit and cost results from the Participant and the Utility Cost Tests, where the rebates or incentives to the participants conceptually cancel each other out. The costs in this test are the program costs paid by both the utility and the participants. This includes incremental customer costs to pay for having more efficient appliances or equipment. Another way to conceptually think about the

TRC test is as follows. With the UCT, any cash flows in or out of the utility building matter. With the TRC test, and cash flows of the utility and the participant. Here, rebates flow between the participant and the utility so they negate each other. Total Resource Cost (TRC) test it is the total benefits over total costs including the participant and utility costs. With that view the lifetime of the benefits for the participant are significant as well as program incentive and administrative costs. This is especially true with the long life measures. Participation is less significant here as the view is primarily one unit and the cost to support that unit.

On low cost items such as Residential CFL's with short lives, low costs and small incentives, the participation and savings estimates become much more important. Overall participation is important for achieving overall program targets for regulatory compliance (saving 35 MW for example) but not as important in the cost effectiveness modeling unless there are heavy fixed costs. As expected, the incentives are much less significant in the TRC Test than shown above for high bay fluorescents in the UCT.

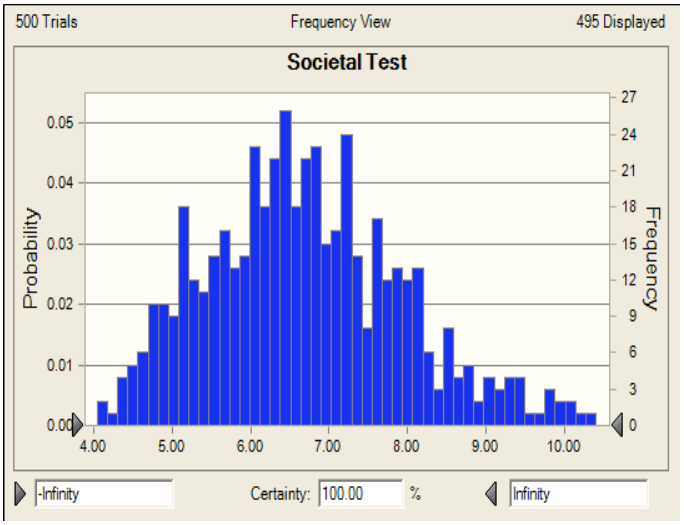
CFL Screw in - Residential

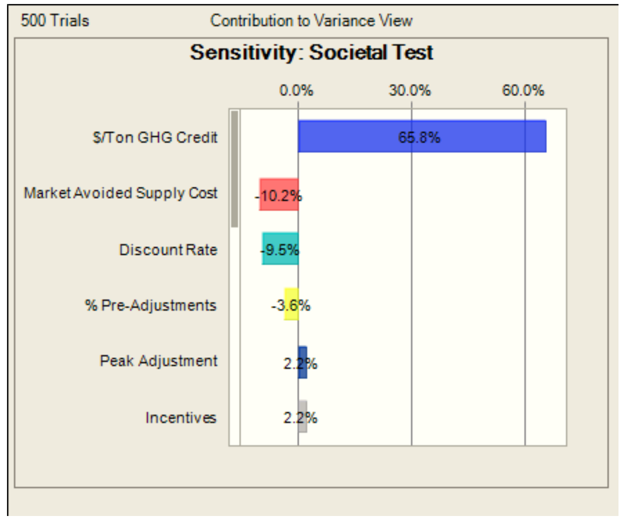


Greenhouse Gas Emissions

Given the emerging importance of Green House Gases, we also looked at the potential significance the green house gas costs via a dollar per ton credit applied to the cost effectiveness results. As you can see below the assumptions used have a significant impact on the Societal Test outcomes. Planners and policy markers will need to carefully consider how green house gas costs are included in EE cost effectiveness testing going forward.

High Bay Fluorescent 6LF32T8





It is encouraging to demonstrate that EE programs can contribute significantly to the overall reductions in greenhouse gas emissions. The table below measures the annual lb reduction in CO_2 emissions and the expected cumulative benefit this represents in dollars.

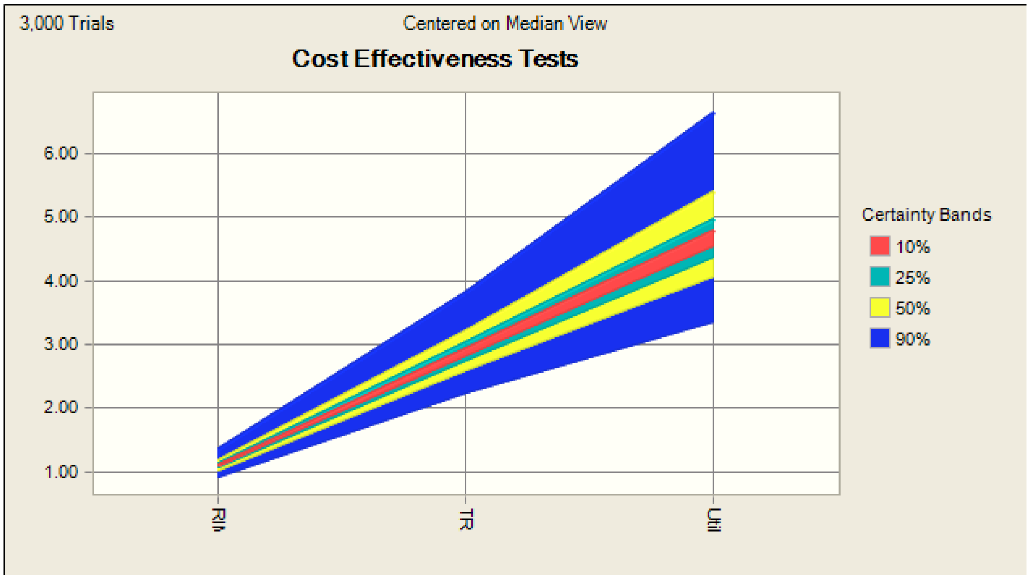
Total Greenhouse Gas Impacts	
Total Per Participant Savings (Lbs)	26229
Total Cumulative Savings (Lbs)	382323530
Total Per Participant Savings ($)	$285.61
Total Cumulative Savings ($)	$4,163,234.49
Total Cumulative NPV Savings ($)	$3,039,119.84

$/Ton GHG Credit
20

Greenhouse Gas Impacts by Year			
Year	Cumulative Participants	LBs CO2	$ CO2
1	3,951	7,402,198	80,605
2	7,981	14,952,440	162,822
3	12,090	22,650,726	246,650
4	16,239	30,423,034	331,285
5	20,407	38,232,353	416,323
6	20,407	38,232,353	416,323
7	20,407	38,232,353	416,323
8	20,407	38,232,353	416,323
9	20,407	38,232,353	416,323
10	20,407	38,232,353	416,323
11	16,456	30,830,155	335,719
12	12,426	23,279,913	253,502
13	8,317	15,581,627	169,673
14	4,168	7,809,319	85,038

Comparing Cost Effectiveness Results

We see considerable uncertainty in the UCT results, more so than the RIM test results, or the TRC results. The plus or minus confidence range of 90%, for example, for the UCT in this case ranges from slightly above 3.0 to about 6.5, whereas the 90% confidence ranges for the RIM tests goes from a low of about .9 to a high of 1.5. The conclusion that we can draw from this chart is that uncertainty is more important when the Utility Cost Test is used as the primary cost-benefit ratio, much more so than if the RIM test were used. This is true even though both tests use the same assumptions surrounding the program parameters.



The distribution of cost-effectiveness results are shown below. The chart demonstrates the range of results that can be expected based on the program planners choice of variables combined with the uncertainty tested by this paper. The low results demonstrate the least cost effective result. That would be the case where market, financial, and program variables all took on their least advantageous possibilities and with mild weather and low price. On the other hand, the most cost effective result is possible when all uncertain variable work to our advantage. The range is a measure of risk associated program implementation, hot weather and high prices. Typically the average result is reported. Distributions with a narrow range are less risky than those with a wide range. In the case of a narrow range, there is more certainty that the average outcome will be realized.

The TRC and UCT distributions for the AC, commercial lighting and residential lighting programs are shown below. As you can see the ranges can be significant depending on the variables used. From a planners standpoint those technologies approaching or equal to one with wide distributions should be the technologies that are looked at most closely to tighten the assumptions used.

	TRC		UCT	
Technology	**Mild Weather Low Price**	**Hot Weather High Price**	**Mild Weather Low Price**	**Hot Weather High Price**
AC 135K - 240K BTU	**1.7**	**4.3**	**2.5**	**7.5**
High Bay Fluorescents	**1.5**	**4.8**	**2**	**11**
CFL Commercial	**2.6**	**6.5**	**1**	**12**
CFL Residential	**1.5**	**4.2**	**2**	**6.6**

Conclusions

In general the results focused on three sources of uncertainty – market based uncertainty, financial uncertainty, and program planning uncertainty. As expected the results demonstrate that weather driven changes in avoided costs, market prices and consumption have a significant impact on the eventual cost effectiveness of a program. The paramount importance of avoided costs perhaps should not come as a big surprise. The whole DSM industry exists because of avoided costs, due in large part to least cost planning mandates. However, it is important to observe that for many programs the weather plays a key role in determining the load reductions, and hence the value of the avoided costs achieved and the test results that are created. Many states tend to overlook the key roles that weather, load reductions and avoided costs jointly play in the optimal selection and pursuit of DSM programs. Unfortunately the program planners cannot directly influence these variables. However, a planner can design the program to account for market uncertainty in a way that assures program success when market based risk works to reduce program benefits.

The results further examined financial risks that are largely driven by the operational uncertainty surrounding the utility. These risks include such things as rate uncertainty, discount rates, losses, escalators to name a few. As a planner you should work with the utility forecasting team to get their assumptions for these key parameters to make sure there are consistencies as well as reasonableness in the assumptions. Doing so will help make sure the result is one more accurate but second these results will then be comparable to the other utility forecasting models.

Greenhouse gas legislation poses a significant risk to utilities in the very near future, and bodes very well for conservation programs that mitigate those risks. We found that the bulk of the value achieved in greenhouse gas avoided tended to occur after the first 500 hours of operation, although it varied hourly and by month. The likely cause in this case is the avoidance of intermediate, non peaking plants which tend to have higher carbon dioxide output than natural gas peakers. DSMore values avoided greenhouse gas based on the utility dispatch stack, analyzed at the hourly level. Averaging type models were not able to pick up this key nuance, and this is important to program planners interested specifically in avoided greenhouse gas valuation for DSM.

When planning EE programs, thorough cost effectiveness modeling is essential to understanding the program structure, incentives, costs and benefits. It is also an important regulatory requirement in many states. With this analysis we tried to understand the most important variables in the cost effectiveness analysis. While we expected to find some variables that are more significant, our research demonstrated that the key variables depend on the measure types, customer load shape affected, and program design. It also depends on the goals to be accomplished and the cost benefit tests being used for decisions. No one variable is the most significant for all situations. For example, administrative costs are important overall but only related to participation if there are significant fixed costs and overheads associated with the program. Incentives are important to the UCT test but not TRC as they are a pass through and not included within the test. Free Rider/Driver levels are important in the UTC and less in the TRC. Utility rates do not enter into the UTC calculations, thus insignificant for this test.

The variation in results indicates that all of the parameters in one way or another are important in designing an effective program. Market, financial, and program parameters all drive value. Although general principles can be observed, it is not as simple as focusing on a single variable at the expense of understanding all of the sources of risk facing program planners. The results indicate that the current efforts nationally to better understand key program parameters are well justified. For example, studies to better define savings, or studies that seek to better quantify avoided capacity costs are needed and will benefit the DSM program planner by removing sources of uncertainty and risk. In the end planners should have a good modeling tool from which to analyze various parameters and assess the risk by program and technology, otherwise program decisions may be made that are not cost effective.