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Developing Cost-Effective Inspection Sampling Plans for Energy-Efficiency Programs at Southern California Edison

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This paper summarizes the results of the development and implementation of a decision model for a major California utility company. The company's program managers use the model to select the most cost-effective sampling inspection plan for managing a portfolio of energy-efficiency programs. The decision model can be used to evaluate the performance of possible sampling strategies based on historical data. We illustrate the application of our decision model to a specific program. We further highlight several key implementation success factors and discuss the benefits that the utility company accrued from using the decision model.

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Energy efficiency in electricity generally refers to the replacement of appliances by more efficient models, home weatherization (e.g., door insulation), installation of energy control systems, design of buildings to incorporate advanced energy-saving technologies, and other actions that can reduce total electricity consumption. In California, energy efficiency is a high-priority objective as the state seeks to meet its growing energy needs in a clean, low-cost manner and reduce its greenhouse gas emissions. The California Public Utilities Commission (CPUC) has designed effective market mechanisms to incentivize public utility companies to encourage consumers to reduce energy consumption. Under these market mechanisms, public utility companies have developed and delivered a portfolio of energy-efficiency programs to their customers.

Southern California Edison (SCE), one of the largest electric utilities in California, serves more than 14 million people in a 50,000 square-mile area of central, coastal, and Southern California. SCE delivers a portfolio of energy-efficiency programs to its customers in various market segments. For example, its statewide home-energy-efficiency rebate program offers rebates to residential customers to cover some of the incremental costs of purchasing energy-efficient appliances.

Energy-efficiency programs are established through a regulatory process under the auspices of the CPUC. SCE needs to submit its program design and budget requirements to the CPUC for approval; in addition, it must periodically submit the outcomes of all its energy-efficiency programs for review. The funding for each program comes from an additional charge on SCE customer bills, which the CPUC must approve. SCE uses this funding to pay for customer incentives, marketing costs, and administrative expenses, including inspections. Although these energy-efficiency programs increase the short-term energy cost that SCE customers pay, the resulting energy savings of the programs help to reduce future investment costs required by SCE to serve its customers; hence, customer energy bills will be lower in the long run.

Customers usually employ contractors to install energy-efficiency hardware or equipment for these programs. The contractors, on behalf of their customers, submit applications to SCE to request incentive payments based on program requirements. SCE reviews the applications and then performs onsite, post-installation inspections to verify the information in the applications. More importantly, the onsite inspections help SCE to gather information to confirm that these programs achieve their stated energy savings and that customers receive the correct incentives based on the equipment or solutions actually installed. However, it would be too expensive for SCE to perform inspections on 100 percent of the equipment installation projects in each program. Therefore, a key task for SCE program managers is to select cost-effective sampling plans to monitor program performance.

Program managers need a decision support tool that can help them to quantify and evaluate the tradeoff between the associated risks and costs for the various sampling-plan options. Because energy-efficiency programs are funded by electricity ratepayers under the auspices of the CPUC, SCE must comply with many regulations and directives in managing these programs. Therefore, these program managers need a tool that provides sufficient flexibility to accommodate the specific operating characteristics of each individual program, because the programs have many qualitative attributes that are difficult to incorporate directly into a quantitative analysis. Furthermore, energy-efficient programs are constantly evolving to adapt to new technological advances in the energy sector; therefore, the decision tool developed must be easy to maintain and revise by SCE management in support of their decision-making processes.

To address the aforementioned challenges that SCE management faces, we developed a decision model that SCE management can use to evaluate the expected performance of various sampling plans and to support it in selecting the most cost-effective method of inspecting installed projects. The most important aspect of the decision model is to allow SCE management to predict the expected performance for any specific sampling plan and support program managers in evaluating the tradeoff in determining cost-effective sampling plans for managing their energy-efficiency programs.

Performance Variables

To effectively manage the incentive payouts and achieve the intended energy savings for all its energy-efficiency programs, SCE monitors, among other factors, three important quantitative performance variables that are closely related to inspection activities: (1) incentive dollars, (2) annualized energy savings (measured in kilowatt-hours), and (3) peak demand reduction (measured in kilowatts). Henceforth, we refer to these three performance variables as incentive dollars, kWh savings, and kW reduction, respectively.

In this paper, we focus on quantifying the program performance associated with these three variables only. Although other aspects, such as quality control, process improvement, and contract management, are also important decision factors in determining the success of the programs, we do not cover them in this paper.

The sampling results associated with any specific inspection strategy are important in monitoring these three performance variables. First, SCE management can use historic data to detect potential abnormalities for future performance. Second, for various reasons, discrepancies between the submitted amount of a performance variable and the actual amount of the performance variable upon inspection are commonly found. Uncertainty is always present in determining the actual values of these performance variables, unless 100 percent of the installed projects are inspected. The sampling results can thus be used to provide some confidence range for these performance variables for each program.

Clearly, selecting a higher percentage of projects for inspection versus the higher costs associated with inspecting a greater number of projects requires making a tradeoff. The main objective of the decision model is to provide useful information on the performance of any specific inspection strategy and its associated inspection cost, so that SCE program managers can use this information, in conjunction with other program-specific characteristics, to determine the most cost-effective sampling plan for managing their energy-efficiency programs.

The Prediction Model

For effective inspection planning, we developed a decision model that we called the prediction model, to predict the performance of any given sampling plan. The prediction model requires two basic sets of user input data. The first set allows the model user, who can be the program manager or one of his (her) associates, to construct a specific sampling plan for evaluation. The model user specifies a list of criteria for selecting a project to be included in the mandatory inspection pool, a pool in which every project is subject to a full inspection. For example, these criteria may include the project size, project characteristics that are more likely to result in discrepancies, experience of the vendors, and any other factors based on the program managers' knowledge of their programs.

If a project is not selected for inclusion in the mandatory pool, it is classified into one of several possible sampling pools. The model user provides the specific criteria for classifying a project into a particular pool and the sampling proportion for each sampling pool. The sampling proportions could differ among the pools. Finally, the model user provides an average inspection cost for a project in the program. For simplicity, the model currently assumes the same average inspection cost across all projects; however, it can be extended easily to allow different average inspection costs for the sampling pools.

The second set of input data allows the model user to specify several key model parameters that define the relationships among the performance variables for the program. Typically, post-installation inspections are used to determine the actual values of these performance variables, which can differ from the submitted values of the variables in the project applications. Depending on the approach used to calculate kWh savings and kW reductions, the volume and type of information that must be collected during the inspection differ. For example, a deemed approach corresponds to standard installations in which the unit values of the three performance variables are fixed based on a list of qualified hardware or equipment, and on the location, building type, and nature of the project. Post-installation inspections are used to verify the eligibility and quantity of the installed hardware or equipment, and the values of the performance variables are determined based on the predetermined fixed value per unit and on the number of units installed. A calculated approach uses an engineering method based on specific measurement and verification protocols; using this approach, more information must be collected during the inspection for which the kWh savings and kW reductions are being calculated.

We make two simplifying assumptions in our prediction model. First, we assume the following relationship between the submitted value (S_j) and the inspected value (I_j) of the performance variable, $\beta_j = I_j/S_j$, where β_js are independent and identically distributed (i.i.d.) random variables with mean b and standard deviation σ_b. The values of b and σ_b are assumed to be the same for all projects within the same sampling pool, but can differ across sampling pools. These values of b and σ_b can be estimated from historic data in the program, and must be specified by the model user as model parameters.

Second, the true value of each performance variable can also differ from the inspected value of the performance variable, because inspections follow strict inspection protocols that usually do not require inspection of every installed element in the project. We assume the following relationship between the inspected value (I_j) and the true value (T_j) of the performance variable $\alpha_j = T_j/I_j$, where α_js are i.i.d. random variables with mean a and standard deviation σ_a. Again, the values of a and σ_a are assumed to be the same for all projects within the same sampling pool, but can differ across sampling pools. These values of a and σ_a must be estimated from historic data and specified by the model user as model parameters. However, SCE does not have readily available data in an electronic format to permit a good estimate. As such, we assume that the true value of each performance variable is equal to its inspected value in all our current applications (i.e., we set $a = 1$ and $\sigma_a = 0$ in all our analyses).

If a project is selected for inspection, the approved value of each performance variable is equal to the inspected value of the variable. Otherwise, the approved value of each performance is simply equal to the contractor's submitted value of the variable.

Using these two relationships, the prediction model can evaluate the performance of a specific sampling plan as defined by the first set of input data provided by the model user. The appendix includes the technical analysis that the prediction model uses.

Model Output

Based on the input data previously described, the prediction model estimates the expected performance of the sampling plan and provides an output summary of the results. Table 1 shows a sample output summary of the prediction model.

First, the output summary shows that the selected sampling plan would require a total inspection cost of $200,500. For this sampling plan, the model predicts that the expected total incentives approved for the program would be $220,000 above the true total incentives that should be paid out for the program, the expected total kWh savings approved for the program would be 3,200,000 kWh above the true total kWh savings achieved by the program, and the expected total kW reduction approved for the program would be 1,000 kW above the true total kW reduction achieved by the program.

Total inspection cost	$200,500		
Average over-approved amount			
Incentive:	$220,000		
kWh:	3,200,000		
kW:	1,000		
Realization ratio			
	Average	Lower range	Upper range
Incentive:	0.97	0.96	0.99
kWh:	0.98	0.96	1.00
kW:	0.99	0.98	1.00
Projects			
	Total #	# inspected	% inspected
Mandatory pool:	500	500	100
Sampling pool A:	900	90	10
Sampling pool B:	2,500	375	15
Sampling pool C:	100	30	30
Total:	4,000	995	25
TRUE kWh savings (in MWh)			
	Average	Lower range	Upper range
Mandatory pool:	88,500	86,200	90,800
Sampling pool A:	16,600	16,200	17,000
Sampling pool B:	51,700	50,700	52,700
Sampling pool C:	4,600	4,400	4,800
Total:	161,400	158,900	163,900
APPROVED kWh savings (in MWh)			
	Average	Lower range	Upper range
Mandatory pool:	88,500	86,200	90,800
Sampling pool A:	17,300	17,200	17,400
Sampling pool B:	54,000	53,600	54,400
Sampling pool C:	4,800	4,700	4,900
Total:	164,600	162,300	166,900

Table 1: A sample output summary of the prediction model shows the total inspection cost, average of the three performance variables, and 95 percent confidence ranges of kWh savings. All numbers shown in the tables are for illustrative purposes only and do not correspond to any specific program.

The output summary also provides the realization ratio for each performance variable, including a 95 percent confidence range, where the realization ratio of a performance variable (i.e., incentive dollars, kWh savings, or kW reduction) is defined as the ratio of the total expected approved value to the total submitted value of the performance variable for the program. For this sampling plan, the expected total incentive approved for the program gives an average realization ratio of 0.97, with a 95 percent confidence range from 0.96 to 0.99, the expected total kWh savings gives an average realization ratio of 0.98, with a 95 percent confidence range from 0.96 to 1.00, and the total kW reduction gives an average realization ratio of 0.99, with a 95 percent confidence range from 0.98 to 1.00.

The output summary also provides detailed information on the total number of projects and the number of projects inspected, and additional information on the three performance variables for the projects in each sampling pool. This example has four sampling pools: the mandatory pool (with 100 percent inspection), and sampling pools A, B, and C.

In Table 1, the prediction model estimates that the expected true total kWh savings for the 500 projects in the mandatory pool are equal to 88,500 MWh, with a 95 percent confidence range from 86,200 MWh to 90,800 MWh. Similarly, the expected true total kWh savings for the 900 projects in sampling pool A is estimated to be 16,600 MWh, with a 95 percent confidence range from 16,200 MWh to 17,000 MWh. Overall, the expected true total kWh savings for all 4,000 projects in the program are estimated to be 161,400 MWh, with a 95 percent confidence range from 158,900 MWh to 163,900 MWh.

The prediction model also estimates that the expected approved total kWh savings for the 500 projects in the mandatory pool is 88,500 MWh, with a 95 percent confidence range from 86,200 MWh to 90,800 MWh. Note that these numbers are the same as those for the expected true total kWh savings; all projects in the mandatory pool must be inspected, because we assume that the inspected values are equal to the true values (i.e., with the user-specified model parameters of $a = 1$, and $\sigma_a = 0$).

Also, the expected approved total kWh savings for the 900 projects in sampling pool A is estimated to be 17,300 MWh, with a 95 percent confidence range from 17,200 MWh to 17,400 MWh. These numbers differ from those for the expected true total kWh savings, because only 10 percent of the 900 projects in this sampling pool will be inspected. Overall, the expected true total kWh savings for all 4,000 projects in the program is estimated to be 164,600 MWh, with a 95 percent confidence range from 162,300 MWh to 166,900 MWh.

An Application

We next describe the implementation for a specific program to illustrate the application of our decision model for selecting a cost-effective sampling plan for this program. This energy-efficiency program aims to improve home-energy efficiency for SCE's residential customers by offering financial incentives for installing approved energy upgrades in the home. Qualified customers can receive incentives from available funds up to a maximum amount. To receive these incentives, a customer needs to make multiple home improvements that work together to increase overall energy efficiency and maximize the long-term energy savings in their homes.

In the most recent program year with post-inspections, the data set included 782 projects. It provides the following key information for the three performance variables (i.e., incentive dollars, kWh savings, and kW reduction): (1) submitted variables before installation, (2) approved variables before installation, (3) submitted variables after installation, and (4) approved variables after installation. The data set also tracks a number of project characteristics, including gross or unit measure cost, facility-floor area, climate zone of the facility, and the vendor performing the installation.

One main objective of our data analysis was to study the amount of discrepancy between the vendor-submitted value of each performance variable and the approved value of that variable upon inspection. In particular, we used the realization ratio of a performance variable, which we defined as the ratio of the approved value to the submitted value of the performance variable, as the key metric of this discrepancy. That is, the approved value of a variable is greater than the submitted value when the realization ratio of the variable is greater than one, and the approved value is smaller than that of the submitted value when the ratio is less than one.

We analyzed the realization ratios for the three variables (kWh savings, kW reduction, and incentive dollars) for the 782 projects with post-inspections. However, we excluded a number of outliers in our analysis. In particular, we removed those data points with realization ratios greater than five. We found that most of these outliers resulted from data entry errors.

We further analyzed how different project characteristics might significantly affect the realization ratios. We performed various statistical tests to identify potential risk factors that can lead to high-discrepancy ratios, and any other important implications that would be of interest to the program manager. For example, we observed that the climate zone of the facility can have a significant impact on the realization ratios of kWh savings and kW reduction. In particular, the realization ratios of kWh savings and kW reduction for two specific climate zones are significantly lower than those for the other climate zones. Climates zones are the 16 geographic areas (defined by zip code) in California for which the California Energy Commission has established typical weather data, prescriptive packages, and energy budgets; see California Energy Commission (2015) for details.

For this program, we were particularly interested in whether there was a learning effect on the vendors such that the discrepancy ratios would improve with experience among these vendors. If so, we would expect the realization ratios for the performance variables to stabilize after the first several projects that these vendors installed. The data set included many vendors. For our data analysis, we focused only on a set of key vendors that had installed at least 20 projects. To study this effect, we examined the realization ratio of each performance variable by project sequence for each vendor, and compared the realization ratios for the first several projects with those of the remaining projects. Overall, we found that a learning effect on the vendors exists. Furthermore, the learning effect diminishes after the first three to five projects for each of the three performance variables. In view of these findings, we recommended performing mandatory inspections for each vendor's first five projects.

We also explored a number of other factors or indicators that could possibly affect the realization ratio of each performance variable. For example, our results suggest that when the submitted incentive dollars after installation are much higher than the reserved incentive dollars before installation, the approved incentive dollars upon inspection are more likely to be smaller than the submitted incentive dollars after installation. Consequently, we recommended that SCE perform a mandatory inspection when the ratio of submitted incentive dollars after installation to the reserved incentive dollars from a project is above a specific threshold value (e.g., 2.0).

Sampling Plan Recommendations

Based on our data analysis, we recommended that SCE management use a stratified random sampling approach to perform inspections for this program. (We refer the readers to Cochran 1977 for background information on stratified sampling techniques.) For example, projects are automatically selected for mandatory inspection if the submitted value of a variable exceeds a certain user-specified threshold value. We also considered mandatory inspections for the first several projects from each contractor to take into account any possible learning effect. We then considered mandatory inspections when the ratio of the amount submitted after installation to the amount reserved before installation for any of the three variables exceeds a threshold value, because discrepancies are more likely in such projects.

Using the model results, we quantified the tradeoff between an increase in accuracy in the approved values for each variable against the associated increase in total inspection costs. Our objective was to select a cost-effective sampling plan for the program. For example, Figure 1 summarizes the trade-off between incentive dollars at risk versus the required inspection cost for implementing a specific sampling plan. We define the incentive dollars at risk as the expected amount of overpayment in incentive dollars using this specific sampling plan as compared to performing a 100 percent inspection. This illustrates that the program manager can choose to use a sampling plan with higher inspection proportions to potentially reduce

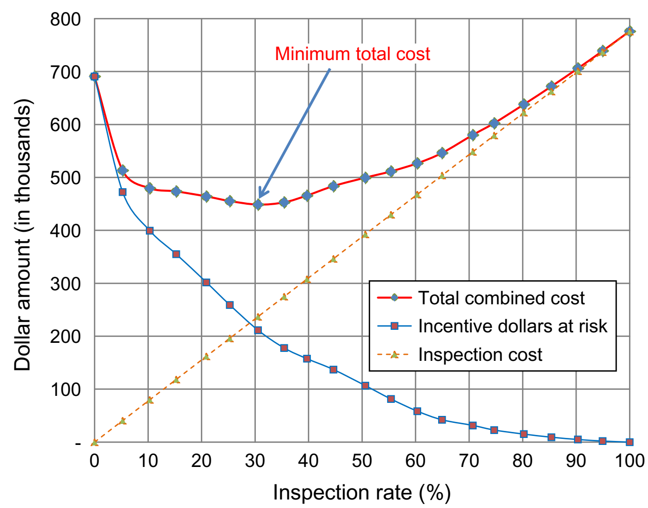

Figure 1: (Color online) A tradeoff analysis between incentive dollars at risk and inspection cost under different inspection rates indicates that a minimum total cost of $449,000 is achieved under a sampling plan with a 30.5 percent inspection rate.

the expected overpayment in incentive dollars; however, this choice comes at the expense of a higher inspection cost.

We used the information shown in Figure 1 to select a cost-effective operating point. Both the incentive amount and inspection cost are paid out of the program budget; therefore, we can consider an optimal operating point as the one that minimizes the combined incentive dollars at risk and inspection cost. In particular, the results in Figure 1 suggest that this combined cost is minimized at $449,000 under a sampling plan with a 30.5 percent inspection rate, which corresponds to an inspection cost of $237,000 and incentive dollars at risk of $212,000.

However, other factors should be considered in evaluating the effectiveness of a specific sampling plan. For example, having an accurate estimate of the true energy savings (in terms of kWh savings and (or) kW reduction) is important. For this factor, the 95 percent confidence range needs to be taken into account in evaluating the performance of a sampling plan. In addition, the program managers need to assess the potential impact of inspections on overall customer satisfaction, because inspections can disrupt customer operations or require customer time and resources to coordinate the inspection schedule. We discussed these factors with the program managers and assigned different weights to these factors in our evaluation of possible inspection strategies. Based on these discussions, we agreed on a sampling plan for the future implementation of this program.

Achieved Benefits

As we previously discuss, the decision model has provided SCE management with useful information about the predicted performance of individual sampling plans, which are important in selecting cost-effective strategies for managing specific energy-efficiency programs. Conversely, the model does not consider other qualitative decision factors. Precisely quantifying the economic benefits of the model is difficult.

To provide a rough estimate of quantifiable benefits, we performed the following simple analysis of a hypothetical scenario. We selected one popular energy-efficiency program, and compared the results of the actual sampling plan used for this program prior to the implementation of the decision model with that of a sampling plan, which would achieve a similar level of performance based on our prediction model. In particular, the actual sampling plan used prior to the model implementation specified conducting mandatory inspections on all projects greater than $15,000 and randomly inspecting 20 percent of the remaining projects in the program. We used the prediction model to estimate the incentive dollar at risk for the program under this sampling plan. We then used the prediction model to evaluate a number of other possible sampling plans, and selected the most cost-effective plan, which could achieve similar performance. This selected sampling plan (with mandatory inspection for all projects greater than $12,000 and random inspection of 11 percent of the remaining projects in the program) could achieve the same level of incentive dollar at risk, but reduces the expected inspection cost by 32 percent as compared to the actual sampling plan used. Using this 32 percent as an average inspection-cost reduction with the implementation of the decision model and multiplying this 32 percent by the total annual inspection costs for all the energy-efficiency programs of $4.5 million, we estimate that the decision model could have provided an annual savings in inspection costs of approximately $1.4 million, while achieving a similar level of incentive dollars at risk for all programs in SCE's energy-efficiency portfolio.

The aforementioned simple analysis can provide only a very rough estimate, because the true cost savings are arguably a complex function of many factors, including the portfolio mix, specific program characteristics, inspection costs, project sizes, targeted realization ratios, budgeted incentive amount, and kWh and kW goals. Using the performance information provided by our decision model, program managers can compare various performance targets to select sampling plans that are most appropriate for their specific program objectives. As compared with their prior decision process, our model also provides valuable intangible benefits to SCE, including an improved level of assurance of its energy-efficiency program performance, and direct tangible benefits, including inspection-cost reduction.

Implementation Success Factors

We successfully demonstrated the value of the prediction model in providing useful information to help SCE management select cost-effective sampling plans for a number of energy-efficiency programs. Next, based on our experience, we summarize a number of important factors that we believe were critical for our successful implementation of the prediction model as a useful decision support tool.

First, gaining user acceptance during the early phase of this project was important. During the first phase of the project, we selected two programs for implementation as a pilot study. We carefully analyzed the most recent available data in each program to understand the operating characteristics of each program, and the impact of various factors on the inspection outcome of all inspected projects in these programs. We discussed our findings with two program managers to ensure that our data analyses were correct and that our findings were consistent with the knowledge and experience of program management. After we were satisfied with our findings, we used these historic data to estimate the model parameters and applied the prediction model to estimate the expected performance for a number of sampling plans for each program. Finally, we discussed the model results and worked with each program manager to select a cost-effective sampling plan for each program. Throughout the development process, we worked very closely with the program managers to gain their acceptance.

Second, maintaining accurate historic data for each program was critical. We used this historic data to define appropriate sampling pools, and to estimate the values of model parameters used in the prediction model. Poor data quality, such as missing values or extreme outliers, would obviously skew the results of our data analysis and reduce their accuracy. To ensure data accuracy, we recommend that users work closely with the relevant frontline personnel responsible for collecting and entering data, and we emphasize the importance of high-quality data. A good understanding of the data-collection process is useful in deciding how to handle those data points deemed unreasonable.

Third, the operating characteristics of each program, such as delivery channel, incentive level, or product offers, could change during a program cycle for various reasons, including changes in external market conditions and the introduction of new energy technologies. Therefore, providing the capability to adapt the prediction model to accordingly handle these changes can be a challenge. This requires that personnel have a good understanding of the underlying statistical analysis of the model and thorough knowledge of the individual energy-efficiency programs.

Finally, developing a close working relationship with system users is essential. We explained the model to users with diverse backgrounds, although many of these users did not have enough time to fully understand the details of the model. Through a number of interactive sessions, we worked closely with key users to demonstrate the model capabilities, and showed them how to use the model results to address issues that might arise in managing their programs. It is important that users gain a high level of confidence in the model capability, before they use it in their decision-making processes.

Concluding Remarks

The prediction model we describe in this paper provides a useful decision support tool that allows SCE management to select an appropriate sampling plan based on individual program objectives and resource constraints. Program managers might also need to consider other qualitative factors that cannot be incorporated directly into the prediction model in evaluating the effectiveness of any specific inspection plan. Such factors include program maturity, collective program team experience, vendor and authorized agent experience, interruption to customer business operations, and relative importance of the programs to the entire energy-efficiency portfolio.

One possible extension of our decision model is to build an optimization framework in which we can (1) assign weights (or scoring criteria) to various performance variables, such as inspection cost, incentive dollars at risk, and accuracy of the energy savings, and (2) construct the objective function to maximize the overall weighted score of the sampling plans subject to various operating constraints, including inspection budget, risk tolerance (in terms of dollar, kWh, and kW), regulatory requirements. The optimization framework can then be applied to select the optimal plan over a feasible set of sampling plans (e.g., systematically constructed at an incremental inspection rate of one percent). However, it remains a practical challenge to incorporate other qualitative attributes into such an optimization framework.

In conclusion, we note that professional judgment and expert knowledge of the overall energy industry is inevitably required during the decision-making process, even with the support of rigorous quantitative analysis and well-defined qualitative attributes. A clearly defined process is necessary to incorporate and manage different internal opinions and make the discussion productive to ensure that SCE management arrives at a final decision. Overall, the use of the prediction model has increased the rigor of SCE's inspection planning process; as a result, it increased SCE managers' confidence in their decision-making processes.

SCE management has widely adopted this decision model in selecting effective inspection sampling strategies for managing its portfolio of energy-efficiency programs. The model has provided demonstrable economic benefits (e.g., inspection cost, incentive dollars at risk) and other intangible benefits (e.g., more accurate energy-savings estimates).

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Appendix A. Prediction Model for SCE Inspection Planning

We present a mathematical model to evaluate the performance of a given sampling plan for SCE inspection planning. Specifically, the prediction model provides confidence intervals for a performance variable, including incentive dollars, kWh savings, and kW reduction, given the submitted values of the variable for all projects in the program under any selected sampling plan. This appendix provides the technical details for deriving these confidence intervals.

Model Input and Notation

Assume that there are a total of N projects in the program, and data set provides the submitted value of the variable of each project. In addition, the user has specified a sampling plan under which each project in the program is classified in one of the stratified sampling clusters based on some predetermined criteria, and the model specifies the sampling proportion for each cluster. For example, the sampling proportion for the mandatory pool is equal to 100 percent.

If a project is selected for inspection, the value of the variable will be determined based on the inspection outcome. We call this the inspected value of the variable. In this case, the approved value of the variable is equal to the inspected value. Otherwise, the approved value of the variable is assumed to be equal to the submitted value. Furthermore, the true value of each performance variable can also differ from the inspected value of the performance variable, because inspections follow strict inspection protocols that usually do not require the inspection of every installed element in the project.

We use the following notation in our model.

$S_j =$ Submitted value of the variable for project j.
$I_j =$ Inspected value of the variable for project j.
$A_j =$ Approved value of the variable for project j.
$T_j =$ True value of the variable for project j.
$p_j =$ Sampling probability of project j.

Model Assumptions

For each project j, we assume the following relationship between the submitted value of the variable and the inspected value of the variable

$$\beta_j = \frac{I_j}{S_j}, \tag{1}$$

where β_js are i.i.d. random variables with mean b and standard deviation σ_b. The values of b and σ_b can be estimated from historic data in the program, and must be provided as model parameters. We further assume that β_j is independent of S_j. We conducted a statistical analysis to support this independence assumption. We collected recent historic data for six programs and computed the correlation coefficient of β_j and S_j for each of the three performance variables. The values of these 18 correlation coefficients range from -0.02 to 0.06, and none of these 18 values is statistically significant at the 0.05 level.

We also assume that the inspected value and the true value of the variable has the following relationship:

$$\alpha_j = \frac{T_j}{I_j}, \tag{2}$$

where α_j's are i.i.d. random variables with mean a and standard deviation σ_a. The values of a and σ_a can be estimated from historic data, and must be provided as model parameters. To simplify the analysis, we further assume that α_j is independent of both β_j and S_j. We also set $a = 1$ and $\sigma_a = 0$ in all our applications because of the lack of data on α_j.

Confidence Interval for the Approved Value

Define the indicator function $1_{inspect}$ as

$$1_{inspect} = \begin{cases} 1, & \text{if the project is selected for inspection;} \\ 0, & \text{if the project is not selected for inspection.} \end{cases}$$

Then, the approved value of the variable for project j is given by

$$A_j = 1_{inspect} I_j + (1 - 1_{inspect}) S_j.$$

That is, the approved value is equal to the inspected value if the project is inspected, and is equal to the submitted value if the project is not inspected. Using Equation (1), we can express the approved value as

$$A_j = 1_{inspect} \beta_j S_j + (1 - 1_{inspect}) S_j. \tag{3}$$

Therefore,

$$E(A_j) = p_j E(\beta_j) S_j + (1 - p_j) S_j = [p_j b + (1 - p_j)] S_j. \tag{4}$$

From Equation (3),

$$\begin{aligned} A_j^2 &= [1_{inspect}\beta_j S_j + (1-1_{inspect})S_j]^2 \\ &= 1_{inspect}^2\beta_j^2 S_j^2 + 2(1_{inspect})(1-1_{inspect})\beta_j S_j^2 + (1-1_{inspect})^2 S_j^2 \\ &= 1_{inspect}\beta_j^2 S_j^2 + (1-1_{inspect})S_j^2. \end{aligned}$$

Therefore,

$$E(A_j^2) = [p_j E(\beta_j^2) + (1-p_j)]S_j^2 = [p_j(\sigma_b^2 + b^2) + (1-p_j)]S_j^2,$$

and

$$\begin{aligned} \mathrm{Var}(A_j) &= E(A_j^2) - [E(A_j)]^2 \\ &= \{[p_j(\sigma_b^2 + b^2) + (1-p_j)] - [p_j b + (1-p_j)]^2\}S_j^2 \\ &= \{p_j\sigma_b^2 + p_j(1-p_j)(1-b)^2\}S_j^2. \end{aligned} \tag{5}$$

The approved value of the variable for the program is given by $\sum_{j=1}^N A_j$, which follows from Equations (4) and (5), has a mean of

$$\mu_A = \sum_{j=1}^N E(A_j) = \sum_{j=1}^N [p_j b + (1-p_j)]S_j, \tag{6}$$

and a standard deviation of

$$\begin{aligned} \sigma_A &= \sqrt{\mathrm{Var}\left(\sum_{j=1}^N A_j\right)} = \sqrt{\sum_{j=1}^N \mathrm{Var}(A_j)} \\ &= \sqrt{\sum_{j=1}^N \{p_j\sigma_b^2 + p_j(1-p_j)(1-b)^2\}S_j^2}. \end{aligned} \tag{7}$$

Then, an approximate 95 percent confidence interval for the approved value of the program can be expressed as $(\mu_A - 2\sigma_A, \mu_A + 2\sigma_A)$.

Confidence Interval for the True Value

Using Equations (1) and (2), the true value of the variable for project j is given by

$$T_j = \alpha_j I_j = \alpha_j \beta_j S_j.$$

Therefore,

$$E(T_j) = E(\alpha_j)E(\beta_j)S_j = abS_j \tag{8}$$

and

$$\begin{aligned} &\mathrm{Var}(T_j) \\ &= [\mathrm{Var}(\alpha_j)\mathrm{Var}(\beta_j) + (E(\beta_j))^2\mathrm{Var}(\alpha_j) + (E(\alpha_j))^2\mathrm{Var}(\beta_j)]S_j^2 \\ &= [\sigma_a^2\sigma_b^2 + b^2\sigma_a^2 + a^2\sigma_b^2]S_j^2. \end{aligned} \tag{9}$$

The true value of the variable for the program is given by $\sum_{j=1}^N T_j$, which follows from Equations (8) and (9), has a mean of

$$\mu_T = \sum_{j=1}^N E(T_j) = ab\sum_{j=1}^N S_j, \tag{10}$$

and a standard deviation of

$$\begin{aligned} \sigma_T &= \sqrt{\mathrm{Var}\left(\sum_{j=1}^N T_j\right)} = \sqrt{\sum_{j=1}^N \mathrm{Var}(T_j)} \\ &= \sqrt{[\sigma_a^2\sigma_b^2 + b^2\sigma_a^2 + a^2\sigma_b^2]\sum_{j=1}^N S_j^2}. \end{aligned} \tag{11}$$

Then, an approximate 95 percent confidence interval for the true value of the variable of the program can be expressed as $(\mu_T - 2\sigma_T, \mu_T + 2\sigma_T)$.

Confidence Interval for the Realization Ratio

We define the realization ratio of the variable for the program as the ratio between the total inspected value and the total approved value of the variable for the program; that is,

$$R = \frac{\sum_{j=1}^N I_j}{\sum_{j=1}^N A_j}.$$

If all projects are inspected, then $A_j = I_j$ for all j and $R = 1$. Thus, R represents the discrepancy, expressed as a ratio to the total approved value of the variable for the program, associated with the given sampling plan.

One possible approach for deriving an approximate confidence interval for a ratio of two random variables is to use Taylor expansions to find approximations for the mean and variance of the ratio; see Kendall et al. (1987, pp. 410–413), for details. We use the following simple approach to find an approximate confidence interval for R.

Using Equations (1) and (3), we can write R as

$$\begin{aligned} R &= \frac{\sum_{j=1}^N \beta_j S_j}{\sum_{j=1}^N \{1_{inspect}\beta_j S_j + (1-1_{inspect})S_j\}} \\ &= \frac{\sum_{j=1}^N \beta_j S_j}{\sum_{j=1}^N \beta_j S_j + \sum_{j=1}^N (1-1_{inspect})(1-\beta_j)S_j}. \end{aligned}$$

We can further rewrite the realization ratio R as

$$R = X/(X+Y),$$

where $X = \sum_{j=1}^N \beta_j S_j$ and $Y = \sum_{j=1}^N (1-1_{inspect})(1-\beta_j)S_j$. Then,

$$\mu_X = E(X) = b\sum_{j=1}^N S_j,$$

and

$$\sigma_X = \sqrt{\mathrm{Var}(X)} = \sigma_b\sqrt{\sum_{j=1}^N S_j^2}.$$

It is also straightforward to derive that

$$\mu_Y = E(Y) = (1-b)\sum_{j=1}^N (1-p_j)S_j,$$

and

$$\sigma_Y = \sqrt{\mathrm{Var}(Y)} = \sqrt{\sum_{j=1}^N \{(1-p_j)\sigma_b^2 + p_j(1-p_j)(1-b)^2\}S_j^2}.$$

Using the previous analysis, we provide an approximate 95 percent confidence interval for the realization ratio R as follows:

$$\left(\frac{\mu_X - 2\sigma_X}{[\mu_X - 2\sigma_X] + [\mu_Y + 2\sigma_Y]}, \frac{\mu_X + 2\sigma_X}{[\mu_X + 2\sigma_X] + [\mu_Y - 2\sigma_Y]}\right).$$

References

California Energy Commission (2015) California energy maps. Accessed May 18, 2016, http://www.energy.ca.gov/maps/renewable/building_climate_zones.html.

Cochran WG (1977) *Sampling Techniques*, 3rd ed. (Wiley, New York).

Kendall MG, Stuart A, Ord JK (1987) *The Advanced Theory of Statistics*, 5th ed. (Charles Griffin & Company, London).

Verification Letter

Nancy C. Jenkins, former Principal Manager of Planning and Compliance at Southern California Edison, writes:

"As requested, I write this letter of support for your project (with Edward Wu) in developing a decision support system for determining cost-effective sampling inspection plans in managing energy efficiency programs at SCE.

"SCE has been managing energy efficiency programs for more than two decades, and has achieved significant energy savings to help alleviate the growing electricity demand of California. SCE managers collectively have extensive experience in developing and managing dynamic programs tailored to meet the customers' needs in our changing markets. As new emerging technologies evolve and more data become available, SCE management wants to further enhance our inspection planning process by quantifying the potential risks and benefits in choosing inspection plans.

"The Prediction Model developed by you and Edward provides us a great planning tool that helps to balance the sampling accuracy and inspection costs, which are the most important quantitative aspects in evaluating the effectiveness of a sampling plan. The model results are extremely helpful for us to understand the risk and cost tradeoffs among different sampling strategies, and allow SCE management to make the informed inspection decisions with the support of appropriate quantitative analysis.

"SCE has now applied the Prediction Model to its energy efficiency programs in selecting inspection plans. We have achieved significant cost savings with the use of the Prediction Model, together with other inspection process improvements. We are also exploring the applicability of this model to other demand side management programs, such as Demand Response programs.

"We would like to thank you for your great efforts in developing this decision support system for SCE, and will keep you posted on any latest developments in the applications of the Model."

Kut C. So is a professor of operations and decision technologies at the Paul Merage School of Business at the University of California, Irvine. He received his PhD and MS in operations research from Stanford University. His research interests are in the areas of operations and supply chain management, design of production and service systems, and queueing systems. He has published more than 40 research articles in major academic journals including *Management Science*, *Operations Research*, *Manufacturing and Service Operations Management*, *IIE Transactions*, *Naval Research Logistics*, *Queueing Systems*, and *European Journal of Operations Research*.

Edward Wu is a senior project manager at Southern California Edison Company. He received his MBA degree from the Paul Merage School of Business at the University of California, Irvine, a bachelor's degree in environmental engineering from Tsinghua University (Beijing, China), and a bachelor's degree in environmental economics and management from Renmin University of China. He also earned professional credentials as a Chartered Financial Analyst, Certified Public Accountant, and Certified Internal Auditor. He has extensive experience in data analytics, business operations, accounting, and auditing, turning data into actionable insights to help organizations make better decisions and improve operational efficiency.