The Application of Survival Analysis to Demand-Side Management Evaluation

Robert D. Bordner and Mark Siegal, Synergic Resources Corporation
Lisa A. Skumatz, Skumatz Economic Research Associates

The estimated useful lifetime of energy conservation measures (ECMs) is a critical input to Demand-side Management (DSM) program cost-effectiveness calculations. Accurate assumptions regarding measure persistence, therefore, are essential in the integrated resource planning (IRP) framework. This paper discusses the theoretical basis of survival analysis techniques as well as the practical application of these techniques to the issue of measure retention in DSM. Based upon the authors' experiences, this quantitative technique offers utility planners numerous advantages in the estimation of measure lives and the analysis of measure removal. This paper summarizes the mathematical foundation for this statistical technique which is widely used in the field of demography but is only recently being applied to the field of DSM. The remainder of this paper includes a case study review of the application of this technique, drawing upon projects with which the authors are familiar. In addition to a synthesis of results from these analyses, the paper explores researchers' experiences using this technique, including issues relating to data availability and quality, and limitations encountered in applying this technique to DSM.

Introduction

At a most fundamental level, impact evaluation seeks to answer two basic questions, including (1) what level of impact may be attributable to a program, and (2) for how long will these impacts (efficiency gains) persist? Each of these basic questions presents unique measurement challenges. Moreover, while the challenges encountered in measuring the impact a program has today are significant, attempting to measure the persistence of these impacts into the future is the subject of even greater uncertainty. And, as other evaluators have noted, previous efforts to quantify the impacts of DSM programs have focused in large part upon first-year savings impacts (Jeppesen and Rudman 1993). Aside from the obvious resource planning implications, the persistence of DSM measures also plays a key role in the customer service attributes of DSM. Measures which do not address customers' energy service needs, and are therefore removed prior to failure, reflect poorly on utility DSM programs and highlight the downside of guiding the technology choice of consumers. As a reflection of the importance of persistence, there has been a substantial increase in attention to this topic during the past two years.

This paper discusses the potential for using survival analysis techniques as a means for evaluating the persistence of DSM program impacts. In doing so, we discuss the methodology behind this approach as well as data needs and limitations. Three case study examples are provided in which survival models were used (or attempted) to analyze persistence and quantify effective measure lives. Finally, we assess the long-term potential for the application of this technique within the DSM program evaluation context.

Persistence: A Framework

The term persistence refers to the sustainability of DSM program impacts (typically, but not limited to, efficiency gains) over time. Conceptually, persistence of savings may be segmented into the following three components:

Technical Degradation. This term refers to a degradation, over time, in the level of technical savings achieved through the installation of a particular DSM measure or a change in customer behavior. In measuring these changes, it is important to identify only that degradation which is incremental to the degradation which would have been encountered with the base-case equipment. Researchers have noted, for example, that the efficiency levels of energy efficient refrigerators degrade over time. However, the crucial question is whether or not the magnitude of such degradation is above and beyond that of a standard efficient refrigerator.

Market Progression. This term refers to the change in baseline equipment efficiencies present in the marketplace. While some DSM planning models take into account changes in the baseline efficiency over the time of the planning horizon, this factor is often overlooked. This issue will become a central focus in the evaluation of market transformation programs.

Effective Measure Life. The third element of persistence, effective measure life, results from the combined effect of (1) technical failure, and (2) the retention of measures (or program-induced energy use patterns). In program planning, this key variable in the Benefit-cost analysis equation is typically based upon engineering estimates and/or perceived in-field operating experience (McRae et al. 1987) and may not reflect actual in-field use or retention patterns. When considering effective measure life, it is important to distinguish between the longevity of the actual measures and the longevity of behavioral changes (and, combinations of these two). Energy Management Systems (EMS), for example, include both a technical component—the electronic control system, and a human component–the programming, operation, and maintenance of the system. Renovation and remodeling have been shown to also have a significant role in the effective measure life (Skumatz and Hickman 1992).

Survival analysis is useful in understanding the third component of persistence identified above—effective measure life.

What Is Survival Analysis?

Survival analysis techniques have their origin in the fields of demography and biostatistics, where survival models are used to quantify life expectancy within human and other biological populations. In addition to providing insight into life expectancy ranges, survival models also aid in understanding the causes of mortality within these populations.

Analytical Techniques

The techniques in survival analysis are different from conventional statistical methods, either parametric or non-parametric, because some survival times from some survival data may not be known. This occurs when some subjects in the study are still "alive" at the time data are collected. Thus, the exact survival times for these subjects are unknown. These are called censored observations. If a measure is still in place at the time of data collection, the ultimate removal date is unknown, and thus it is treated as a censored observation. The survival analysis techniques applied to DSM, therefore, take into account the fact that not all measures have failed when data were collected,

The life table method is one type of statistical model that contains several related mortality measures. One of the main advantages of the life table method over other methods of measuring failure rate (mortality) is that this approach does not reflect the effects of the age distribution so that failure rate comparisons among different measures can be made. An observation in the data set can have a different date of installation and/or removal from others. Another main advantage of using life tables is that the statistics provided in life tables can be used for forecasting.

There are two types of life tables: a longitudinal life table and a period life table. The period life table is capable of including multiple years of data in one life table and generating meaningful statistical estimations from these observations even though the data are from different cohorts. The period life table is a mathematical model of the life history of a hypothetical cohort. The key assumption underlying a period life table is that the hazard function (age-specific failure experiences) during the current time represents the failure experience of the whole cohort. That is, we assume the failure rate of one type of measure installed five years ago to be the same as the failure rate for a measure installed four years ago. This assumption may need to be altered, of course, if one has reason to believe that the character of installations has changed over time.

The following statistical estimates are generated in the life table analysis and are used to assess measure retention:

Survivorship Function. This function, denoted by S(t), is defined as the probability that a measure lasts longer than t: S(t) = P (a measure lasts longer than t). In practice, the survivorship function is estimated as the proportion of measures functioning longer than t:

$$S(t) = \frac{\text{No. of measures functioning longer than } t}{\text{Total number of measures}}$$

S(t) is also known as the cumulative survival rate.

Probability Density Function. Like any other continuous random variable, the survival time T has a probability density function defined as the limit of the probability that a measure fails in the short interval t to $t+\Delta t$ per unit width Δt, or simply the probability of failure in a small interval per unit time. It can be expressed as

$$f(t) = \lim_{\Delta t \to 0} \frac{P\{\text{a measure failing in the interval } (t, t+\Delta t)\}}{\Delta t}$$

In practice, the probability density function f(t) is estimated as the proportion of measures failing in an interval per unit width:

$$f(t) = \frac{\text{No. of measures failing in the interval beginning at time } t}{(\text{Total number of measures})\ (\text{Interval width})}$$

The probability density function is also known as the unconditional failure rate.

Hazard Function. The hazard function h(t) of survival time T gives the conditional failure rate. This is defined as the probability of failure during a very small time interval, assuming that the measure has functioned to the beginning of the interval, or as the limit of the probability that a measure fails in a very short interval, t to $t+\Delta t$, given that the measure has functioned to time t.

$$h(t) = \lim_{\Delta t \to 0} \frac{P\{\text{a measure of age } t \text{ fails in the time interval } (t, t+\Delta t)\}}{\Delta t}$$

The hazard function can also be defined in terms of the survivorship function S(t) and the probability density function f(t):

$$h(t) = \frac{f(t)}{S(t)}$$

In practice, the hazard function is estimated as the proportion of measures failing in an interval per unit time, given that they have functioned in the beginning of the interval:

$$h(t) = \frac{\text{No. of measures failing in the interval beginning at time } t}{(\text{Total number of measures})\ (\text{Interval width})}$$

The hazard function is also known as the instantaneous failure rate or conditional failure rate.

Effective Sample Size. The effective sample size n'(t) has the following definition:

$$n'(t) = n(t) - \frac{w(t)}{2}$$

where n(t) is the sample size and w(t) is censored observations. The effective sample size is the key concept in life table survival analysis. It is the effective sample size that makes adjustment for censored data.

Conditional Probability of Failure. The conditional probability of failure q(t) is defined as total number of failures in each age interval divided by the effective sample size:

$$q(t) = \frac{d(t)}{n'(t)}$$

where d(t) is the total numbers of failure in each age interval.

Lifetable Results

In applying survival analysis techniques, a series of life tables is constructed for each of the measures included in the study. From these life tables, we are able to examine patterns in measure retention in greater detail than is possible through more simplistic univariate analysis techniques. Table 1, below, summarizes the major statistical estimations from the life tables. Specifically, the following are shown: (1) Probability of Survival, and (2) Mortality Patterns.

Table 1. Survival Analysis Results: Example

Years (Midpoint)	Survival	Hazard
0.5	1.00000	0.00194
1.5	0.99807	0.00974
2.5	0.98839	0.02778
3.5	0.96132	0.01827
4.5	0.94391	0.03758
5.5	0.90909	0.04489
6.5	0.86917	0.05195
7.5	0.82517	0.04831
8.5	0.78624	0.06098
9.5	0.73972	0.07634
10.5	0.68533	0.11806
11.5	0.60893	0.09524
12.5	0.55357	0.13793
13.5	0.48214	0.56646

Probability of Survival. Using the survivorship function generated in the life tables, it is possible to estimate the probability that, at any given time following installation, the measure will still be in place. This probability is also referred to as the "Survival Function Estimates. " Effective measure life is usually estimated to be that point in time at which the probability of survival is equal to 50%. In Table 1, this occurs at approximately year 12 following installation.

Mortality Patterns. Using the lifetable statistic called the Hazard function, it is possible to identify trends in measure failure over the life of a measure. In other words, at what time during the life of a measure is failure most likely to occur? Mortality patterns have been explored for each of these measures using instantaneous failure rates for each age interval, as represented by the hazard function. The value of the hazard function for each year can also be compared with more traditional engineering estimations.

Data Requirements and Issues

The data required for survival analysis are, conceptually, relatively straight forward. At the most basic level, we need to know the following information pertaining to the original installation:

- what measure was installed,
- when the measure was installed,
- where the measure was installed.

This information is then matched, on a measure-by-measure basis, to ascertain whether or not the measure is still in place. If the measure is still in place, we need to know (1) is the observed measure the original installation, and (2) is the measure continuing to function properly and as intended? If the measure is not in place, we need to know (1) the approximate date of removal, and (2) the reason for removal. Other information which, although not strictly needed for the survival analysis, is useful in evaluating the appropriateness of program expenditures, include:

- what is the condition of the observed measure?

- if the measure has been replaced, what has replaced it? Is the replacement measure more efficient or less efficient than the program-installed measure? Was the replacement measure installed through a utility-sponsored program?

- if the measure has been replaced, what is the disposition of the replaced equipment (e.g., is it still operating, but in another location)?

These follow-up questions can help a utility assess whether it should continue to account for savings because the measure is still being used in another location, but recognize the fact that different operating hours/conditions may exist.

Data Collection Issues and Challenges

While simple in concept, the collection of reliable data is not a trivial matter. Numerous challenges have been encountered thus far, as discussed below.

Conflicts Between Database Records and Customer-Supplied Information. Example: The program database indicates a CFL installation, but the customer insists that the measure was never installed. Or, conversely, although there is no record of a low flow showerhead being installed in the home visited, the customer insists that one was installed through the program.

In such cases, we have generally used the database of record as a relatively strict reference point. In some persistence work, however, evaluators have attempted to account for all variations, both "positive" and "negative" variances. In studying long-term measure retention, it is imperative that issues pertaining to persistence be distinguished from those of overall data quality. The latter should be examined early in the program implementation through process evaluations in order to ensure the fundamental integrity of the database which is being used for measure retention purposes.

Which Measure Is Which. Example: Two lamps are reported installed, one in the kitchen, another in the living room. One lamp is observed in the basement. Or, 200 energy efficient lighting fixtures are reported installed in a 200,000 SF building. 125 energy efficient fixtures are located, only half of which are the type noted in the program records.

While manageable in the residential setting, this type of problem becomes unmanageable quite quickly when dealing with large commercial installations. Indeed, without program records indicating where measures were installed, it may be virtually impossible to ascertain with certainty the true disposition of the installation. In this case, survival analysis is not going to be possible, and evaluators can only report results at an aggregate level (e.g., 83% of lamps installed were accounted for).

Measure Has Been Removed, but the Date Is Unknown. While the optimal situation from an analysis perspective would include a date for removal, this is not a realistic expectation in many cases. For residential participants, removal dates may be known, particularly if the date coincides with a memorable event in the household. And, in some cases, such an event may be directly related to the reason for removal as well, such as "remodeling of the bath." In the commercial and industrial settings, this again becomes problematic because, unless detailed records are kept (and accessible for evaluation purposes), such information is often in the memory of one individual who may or may not be available to interview.

When Has a Measure Truly Failed. Example: Two tank wraps are observed, On one tank, the sealing tape on the top third of the tank wrap has come undone? On the other tank, the top half is undone? Which measure has "failed?"

For some measures, it may be difficult to ascertain exactly when a measure has in fact "failed." In addition, for long-lived measures, it may be useful to distinguish between strict failure and partial failure. While always subjective, it is important in these cases to establish consistent yardsticks by which a measure will be determined to have failed or been removed.

Accounting for "Re-purchase. Example: A grocery has been remodeled, but the energy efficient refrigeration equipment has been replaced with newer state-of-the-art energy efficient equipment. Or, in a residential bathroom, CFLs installed through the program are removed but there is a newer CFL installed in its place.

For utilities which are able to take credit for customer re-purchase (i.e., replacement of failed energy efficient equipment with similar high efficiency equipment), it may be important to not treat these observations as failures. However, from an analytic perspective, treating these as "survivors" may distort the true "effective measure life" estimate.

Case Studies

Summarized below are the results from three persistence studies completed by the authors, in which survival analysis techniques have been applied. In each case, survival analysis has been used to develop effective measure life estimates. The results of these applications suggest significant lessons learned for program evaluators.

Case Study #1: Northeast Utilities Wrap-Up/Seal-Up Measure Retention Study

For Northeast Utilities (NU), SRC conducted a comprehensive measure retention study of participants in the utility's Wrap-up/Seal-up (WU/SU) program (SRC 1993). The WU/SU program installed hot water conservation measures in over 60,000 homes during the period 1981 - 1989. The scope of this study included 600 on-site visits to residences that had been treated through the program.

In this study, the effective measure lives for DHW tank wraps and low flow showerheads were found to be substantially longer than originally planned (Bordner et al. 1993). A summary of the statistically derived measure life estimates from this study are summarized in Table 2.

The removal of hot water wraps was found to occur most often at the time of water heater failure. This study also found that, as had been observed in the commercial sector, renovation or remodeling is cited as the cause of removal for measures—in this case low flow showerheads. Figures 1 and 2 illustrate the survival and hazard curves for each of the measures observed in the study.

Case Study #2: Long Island Lighting Low Income Program Evaluation

As part of a process evaluation for Long Island Lighting Company (LILCO), SRC conducted on-site visits with 45 participants in a low income program (SRC 1994). Survival analysis was used to assess the measure life of compact fluorescent lamp installations. The mean lifetime *interval* estimate for CFLs, at a 95% confidence level, was estimated to be 4.9 years to 8.3 years, with a point estimate of 6.2 years.

However, in this analysis the program had only been in the field for 12 months and the number of failures was limited. Based upon the data which were available, forecasting techniques were used to calculate an effective measure life for CFLs. Using forecasting techniques to calculate an effective measure life for CFLs requires that the analyst assume that the remaining CFLs will experience the same physical and social/economic conditions in the next several years as were experienced in the first year. This assumption introduces additional risk because short term data is used to make long-term assessments.

A summary of the lifetable generated in this study is provided in Table 3.

Case Study #3: Bonneville Power Administration Measure Life Study II

The Bonneville Power Administration has conducted research on measure lifetimes since at least 1987, and has sponsored two recent studies specifically addressing issues related to effective measure lifetimes in the commercial sector. In the most recent study, data from over 600 site visits with commercial customers were used by evaluators in quantifying measure lives for specific equipment types. This study focused on three business types—grocery,

Table 2. Comparison of Engineering Estimates and Survival Analysis Estimates

Retention Measures	Lifetime Estimates: Engineering Estimate (years)	Lifetime Estimates: Survival Analysis (years)	Notes
Tank Wrap	7	12.8	This estimate is directly from the life table.
Pipe Insulation	25	12.5	Extrapolation was used to calculate this estimate.
Low-flow Showerhead	10	14.5	Extrapolation was used to calculate this estimate.

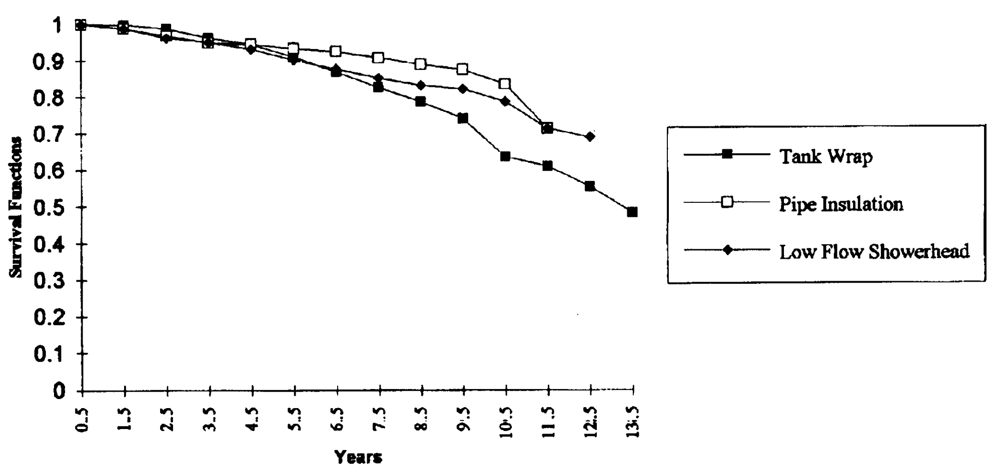

Figure 1. Survival Function Estimates: Hot Water Efficiency Measures

office, and retail because of (1) significant program expenditures in these building types, (2) a large number of buildings, and (3) indications of possible volatility from earlier measure life studies. Survival analysis was employed as one means of quantifying the observed measure lives.

In the BPA study, site visits were completed with buildings drawn from three sources which had been visited previously within the last 2-5 years, including (1) participants in the BPA Commercial Incentives Pilot Program, (2) participants in the BPA Commercial Audit program, and (3) a sample of participants from the Pacific Northwest Non-residential Survey. This last source, a representative survey of non-residential buildings throughout the region, provided a database that could be used to derive generalizable estimates what were more statistically representative of building changes and measure lifetimes. The use of the CIPP database increased the number of "progra.m installed" measures included in the sample. During site visits conducted by experienced energy auditors, it proved to be extremely difficult to match original equipment records (from survey or program participation records) with equipment observed on-site. Matches were few, either in terms of equipment type or counts. Table 4 shows the extent to which exact equipment matches were observed, controlling for an exact count match, and allowing for differences in counts.

Since a strict application of survival analysis requires a matching of records, any non-matches would generally be interpreted as removals. However, using this assumption would result in measure lifetime estimates that were unreasonably short and not credible. Further, it requires

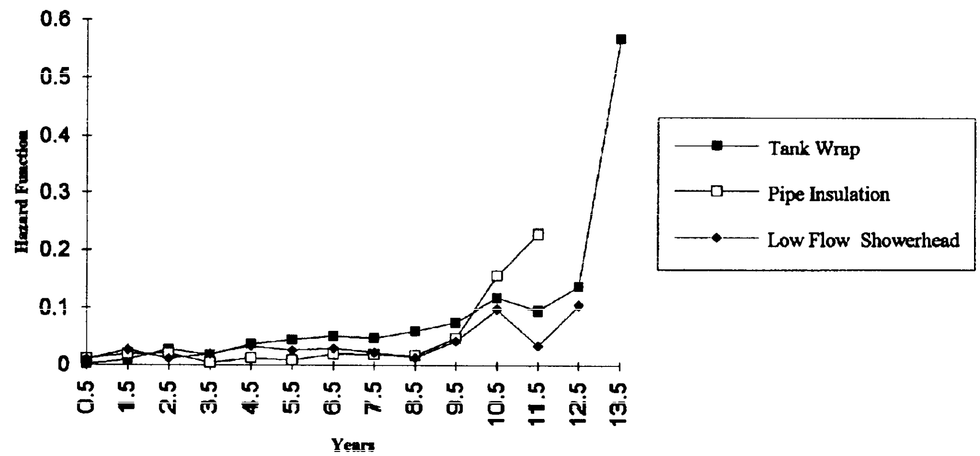

Figure 2. Hazard Function Estimates: Hot Water Efficiency Measures

Table 3. Life Table: CFL Measures

Months	Number Failed	Number Censored	Effective Sample Size	Conditional Probability of Failure	Probability of Survival
0	5	0	220.0	0.02	1.00
1	3	0	215.0	0.01	0.98
2	0	39	192.5	0.00	0.96
3	3	57	144.5	0.02	0.96
4	0	20	103.0	0.00	0.94
5	2	26	80.0	0.02	0.94
6	0	24	53.0	0.00	0.92
7	0	11	35.5	0.00	0.92
8	0	10	25.0	0.00	0.92
9	2	0	20.0	0.10	0.92
10	0	5	15.5	0.00	0.83
11	0	5	10.5	0.00	0.83
12	0	8	4.0	0.00	0.83

ignoring a number of factors related to data collection for the study:

- the original program records were not designed to support measure life analysis, and did not maintain consistently detailed information on measure, types, and dates. Further, specific DSM measures were few in number since only one of the databases was based upon measure installations as opposed to audits of equipment;

- the measure were not followed up between installation and revisit, a period of between 2-5 years (with resulting loss of information regarding dates, disposition, failures, and identification); and

- none of the specific measures installed were tagged in any way to facilitate identification of specific measures.

Table 4. Percentage of Equipment from CIPP, CAP, and PNNonRES Databases Found On-site in MLS II

Equipment Type	Type and Number Match	Type Only Match
Indoor Lighting	18.2	61.1
Outdoor Lighting	25.6	52.0
Water Heating	49.1	72.9
Ventilation	48.4	54.1
Refrigeration	31.0	51.6
HVAC Controls	63.9	63.9
Heating	27.2	42.7
Cooling	35.4	62.0
Cooking	31.3	39.3

The non-matches could not reasonably be assumed to represent failures alone, but could easily be interpreted to include the influence of other factors. In summary, very few matches were possible and the data were not of sufficient quality to rely solely on the survival analysis method for deriving measure lifetime estimates (Skumatz and Hickman 1994). Only a limited survival analysis, on a few lighting measures, was possible; the results from these analyses showed very wide confidence intervals. Despite data difficulties, the study did generate estimates of measure lifetimes using several different analytical methods.

This experience highlights a key limitation of survival analysis-data quality and detail. Particularly when dealing with large numbers of installed measures or measures installed in large complexes, it may be extremely difficult to account for all measures installed. On-site time limitations, site accessibility, on-site sub-sampling strategies, database errors, and other factors may all limit the ability to match records.

The results demonstrate different levels of reliability and robustness, depending upon the measures considered, the analysis used, and the data available. It was found that, absent sufficient data on failures to support survival analyses, other methods can be applied to estimate measure lifetimes for equipment that has reached steady-state replacement rates. However, these techniques fail when examining new, cutting-edge technologies-the very types of equipment likely to be encouraged through utility-sponsored DSM. The advantages of survival analysis techniques are especially useful in these applications but require good recordkeeping. Routine follow-up for a sample of measure installations may be one of the best, and most cost-effective, means of obtaining estimates for commercial measures.

Implications: Opportunities and Limitations

With survival analysis, program evaluators have available a powerful analytical methodology for assessing the effective measure life of ECMs. Moreover, with this technique, relative impacts of various causes of failure can also be quantified. However, as discussed below, the ultimate applicability may vary from sector to sector and may depend upon the types of measures addressed.

Residential Sector

DSM programs targeting the residential sector may lend themselves most easily to the data requirements of survival analysis. In this sector, evaluators are typically working with single-measure installations. ECMs such as (1) hot water wraps, (2) low flow shower heads, (3) energy efficient refrigerators, (4) energy efficient freezers, and (5) attic insulation are relatively easy to identify. Also, use patterns are likely to be fairly homogeneous (within housing types) across large populations. Residential evaluation may not be as easy, however, for low cost weatherization measures such as caulking and other air-sealing steps.

Commercial Sector

Depending upon the types of measures installed, and the variety of facilities retrofit, survival analysis techniques may not be feasible for programs targeting the commercial sector. With lighting ECMs, the sheer volume of measures typically installed will generally preclude the detailed record-keeping required to match program records with on-site observations. Analyses may need to be conducted at a more aggregate level—perhaps the whole facility level, with judgementally-based assessments of measure retention. In this case, measure retention (including potential removal causes such as facility remodel or tenant turn-over) would have to be analyzed at a whole-facility level rather than measure-specific level. Or, as a compromise, data could be collected at a facility zone level and persistence evaluated at a similar level of analysis.

Industrial Sector

Within the industrial sector, it may be possible to apply survival analysis techniques. Long measure lives are typical in this sector, and few failures are likely to be observed within early years. However, within this sector in particular, equipment migration (motors, for example) may come into play and confound efforts to assess effective measure life.

Advantages of On-going Persistence Research

For those settings where data quality is likely to hinder the success of the analysis, it may be worthwhile to conduct on-going persistence research with a smaller sample of customers. In contrast with a larger-scale retrospective study, such an approach would contact a fixed set of customers on a periodic basis (e.g., annually) in order to assess persistence. The advantages of this approach include (1) the ability to identify more precisely the date at which persistence was affected, (2) the ability to maintain contact with facility managers familiar with the measure installation, and (3) the collection of "real-time" persistence data. Despite the long-term commitment required in such an undertaking, we believe that this approach may provide higher quality results for persistence research, in general, and may actually result in long-term cost savings.

Summary

The application of survival analysis shows promise for DSM evaluation. The technique is forgiving and flexible in that it can be applied to measures after relatively short in-field life. Given appropriate data, it can be appropriately applied to measures with high turnover. The method can provide reliable estimates and confidence intervals. However, with its reliance on matched equipment, this method is data intensive, and may require dedicated studies or programs willing to do a great deal of additional monitoring. Absent such data, and the ability to match installations on a measure-by-measure basis, the reliability of survival analysis techniques declines markedly.

From a practical standpoint, the method may have little applicability in lighting programs which have focused on lamps only, as opposed to whole-fixture replacement (where much of early DSM expenditures have been spent) because of the difficulty of monitoring key lighting equipment. Although theoretically appropriate for measures with high turnover, it can be difficult to assure accurate data collection to support reliable quantitative estimates in the case of much changed-out equipment (e.g., lamps). In the case of newer equipment, the measures may or may not have had sufficient field time to generate enough failures to support derivation of lifetime estimates from this method, but results on the same data would generally be better quality than those derived through other simpler estimation methods.

Other methods, including methods relying on information on age of equipment; building age with equipment change information; reported equipment changes; and other methods have several advantages. They are less data intensive, and estimates of measure lifetimes may be derived with data from a single visit in some cases. In addition, for some methods, estimates can be derived with a relatively few observations. However, these methods have several weaknesses and it can be difficult to derive reliable confidence intervals for the measure life estimates.

Based on an assessment of the theoretical and practical aspects of alternative approaches to measure life estimation, it appears that:

- for some measures, simpler analysis methods provide acceptable estimates
- for easily identified measures with few installations per site (e.g., water heaters), it may be possible to support survival analysis using existing program records coupled with an on-site or other follow-up
- for large, singular, or low sample size items that are relatively easily identified on-site, it may be best to pool across programs/utilities to increase the sample size
- for lighting, survival analysis will likely require changes to programs to mark or identify installed measures (including floor plan identification) to support survival analysis
- for newer measures, survival analysis is likely to be necessary in order to derive estimates that reflect more than market tenure, but it will be necessary to design needed data into programs
- it is likely that survival analysis estimations of a range of residential and commercial measures can be supported using a tag system and callbacks rotated with on-site visits.

Survival analysis provides a high quality, credible estimation method, but given its significant data requirements, may be impractical for some measures unless the data collection needs to support estimation of measure lifetimes are designed into DSM programs. However, given the large impact that changes in measure lifetimes may have on cost-effectiveness calculations, it may be important to modify upcoming programs to support these types of efforts until reliable estimates of on-site effective lifetimes can be generated.

References

Bordner, Robert D., Jay Makati, Wei Zhang, and Edie Kinsley. 1993. "Ten years Later: Are the Measures Still there and producing Savings? Lessons from the Field." Energy Program Evaluation Conference, Chicago, IL.

Cox, D. R., and D. Oakes. 1984. Analysis of Survival Data. Chapman and Hall, London.

Jeppesen, John C., and Monica Rudman. 1993. "Measure Life Research: Options and Lessons." National Energy Program Evaluation Conference, Chicago, IL.

Lee, E. T. 1980. Statistical Methods for Survival Analysis. Lifetime learning Publications, Belmont, CA.

McRae, Majorie, et al. 1987. Service Life of Energy Conservation Measures: Final Report, Xenergy, Inc. and Ecotope, Inc. Bonneville Power Administration, Portland, OR.

Palmore, James A. 1986. Measuring Mortality. Fertility, and Natural Increase. East-West Population Institute, Honolulu, HI.

Skumatz, Lisa A., and Curtis Hickman. 1992. "Measure Life Study: The Effect of Commercial Building Changes on Energy Using Equipment. *1992 ACEEE Summer Study on Energy Efficiency in Buildings*, Berkeley, CA.

Skumatz, Lisa A., and Curtis Hickman. 1994. "Effective ECM Measure Lifetimes in Commercial Buildings: Calculations and Analysis of Impacts." *1994 ACEEE Summer Study on Energy Efficiency in Buildings*, Berkeley, CA.

Synergic Resources Corporation. 1993. Measure Retention Study: Wrap-Up/Seal-Up Program, Final Report. Prepared for Northeast Utilities Service Company, Berlin, CT.

Synergic Resources Corporation. 1994. ULIEEP Process Evaluation. Prepared for Long Island Lighting Company, Hicksville, NY.