Energy and Buildings 154 (2017) 430–447

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

Efficient metering and surveying sampling designs in longitudinal Measurement and Verification for lighting retrofit

Herman Carstens[a,*], Xiaohua Xia[a], Sarma Yadavalli[b]

[a] Centre for New Energy Systems (CNES), Department of Electrical, Electronic, and Computer Engineering, University of Pretoria, South Africa
[b] Department of Industrial and Systems Engineering, University of Pretoria, South Africa

ARTICLE INFO

Article history:
Received 13 April 2017
Received in revised form 21 July 2017
Accepted 27 August 2017
Available online 31 August 2017

Keywords:
Bayesian
Retrofit
Dynamic Linear Model
Measurement and Verification
Mellin Transform
Persistence
Metering
Survey
Sampling

ABSTRACT

Measurement and Verification (M&V) is often required for energy efficiency or demand side management projects in buildings, to demonstrate that savings were in fact achieved. For projects where sampling has to be done, these costs can be the most significant driver of the overall M&V project cost, especially in multi-year (longitudinal) projects. This study presents a method for calculating efficient combined metering and survey sample designs for longitudinal M&V of retrofit projects. In this paper, a building lighting retrofit case study is considered. A Dynamic Linear Model (DLM) with Bayesian forecasting is used. The Bayesian component of the model determines the sample size-weighted uncertainty bounds on multi-year metering studies, with results from previous years incorporated into the overall calculation to reduce forecast uncertainty. The DLM is compared to previous meter sampling methods, and an investigation into the robustness of efficient sampling plans is also conducted. The Mellin Transform Moment Calculation method is then used to combine the DLM with a Dynamic Generalised Linear Model describing the uncertainty in survey results for the longitudinal monitoring of lamp population decay. A genetic algorithm is employed to optimise the combined sampling design. Besides the reliable uncertainty quantification features of the method, results show a reduction in sampling costs of 40% for simple random sampling, and approximately 26.6% for stratified sampling, as compared to realistic benchmark methods.

1. Background

Energy Measurement and Verification (M&V) is the process by which energy savings from Energy Efficiency or Demand Side Management (EEDSM) projects (most often implemented for buildings) are independently and reliably quantified [1]. For example, 500,000 Compact Fluorescent Lamps (CFLs) may have replaced their incandescent counterparts in a countrywide residential mass roll-out programme. For such a project to be eligible for tax rebates such as the 12L incentive in South Africa [2] or the United Nations Clean Framework Convention for Climate Change (UNFCCC) Development Mechanism (CDM) programme [3], an M&V team would be asked to quantify the savings realised. The output of an M&V report is an estimate of the energy savings achieved by the project. This figure must usually be reported with regulator-specified degree of statistical precision, which in turn determines the level of monitoring required. The statistical precision is stated in terms of an 'expanded uncertainty', such as 90/10. This means that the 90% confidence bounds on the estimated savings should be within 10% of the mean.

Because the energy saving of a project represents the absence of energy use, it cannot be measured directly. Rather, energy measurements are made or samples are taken during the pre- and post-retrofit periods. An energy model is constructed (or 'trained') using pre-retrofit data, and is then used to predict what the energy use during the post-retrofit period *would have been*, had no intervention taken place. The difference between these values and the measured values is the energy saving.

There are three main uncertainty drivers in such an M&V model which need be accounted for to report savings with realistic statistical precision. These are measurement, sampling, and modelling uncertainty. Controlling these uncertainties can be expensive. In longitudinal studies, metering and sampling uncertainties are the main cost drivers. Many meters need to be installed, and multiple inspectors need to visit geographically diverse sites to install meters and inspect the number of surviving retrofit units. The M&V cost due to minimising metering and sampling uncertainty may even affect the retrofit project feasibility. For example, Michaelowa, Hayashi, and Marr [4] document that no lighting retrofit projects were undertaken under the stringent CDM AM0046 [5] require-

* Corresponding author.
E-mail address: herman.carstens@up.ac.za (H. Carstens).

http://dx.doi.org/10.1016/j.enbuild.2017.08.080
0378-7788/

ment. Only when the alternative AMS II.C [6] and AMS II.J [7] were adopted, did M&V stringency requirements allow for project feasibility and significant uptake. The same effect is present in other M&V projects. Therefore, a research gap exists for methods that can design statistically and financially efficient M&V plans: plans which achieve the same precision as other plans, but at a lower cost in terms of units sampled and money spent [8]. Such methods would not only increase M&V accuracy, but also project profitability. Bayesian methods have been recommended for such situations where finances and uncertainty interact [9]. Efficient methods should also consider measurement, sampling, and modelling uncertainty simultaneously, and trade them off against each another. The need for efficient M&V designs is especially acute in multi-year (longitudinal) M&V studies. Although they are also costly themselves, longitudinal studies have been found to reduce the reported cost of savings by up to 70%, compared to single-year M&V studies [10]. In such longitudinal studies, information from previous years could be used to reduce current and future uncertainties in the savings estimates or to reduce sample sizes. Although this is a common problem, it does not have a straightforward solution for efficient sampling design. Research addressing these gaps will, therefore, enhance both the theory and practice of M&V.

As in the example above, this paper will focus on multi-year lamp retrofit projects in which incandescent lamps are replaced by Compact Fluorescent Lamps (CFLs). Lamp retrofit projects are popular in M&V as case studies [1,11–13], since the operation of lamps is simple, they are mostly independent of covariates such as outside air temperature, and they are well-studied; not many technologies have such readily available data on persistence as CFLs do, for example. They, therefore, serve as a useful introduction to a method, which can be extended later to include considerations such as covariates or other complicating factors.

Such longitudinal energy monitoring projects have two components or dimensions that need to be considered when calculating total energy use and uncertainty, and therefore when designing such studies. The first is population survival: establishing how many of the originally installed (retrofitted) units are still effective at a given point in time. This entails survey sampling and has been the focus of previous works [14–20]. The second factor is the average annual energy use per unit. For lighting studies, this can be calculated with measured operational hours by lighting loggers and estimated power use of lamps. In M&V jargon this is called the ‘retrofit isolation with key parameter measurement’ approach [1]. Alternatively, meters may be installed on a sample of the lighting circuits, which is called ‘retrofit isolation with all parameter measurement’. Even though metering is cross-sectional (in the spatial dimension), there is still a longitudinal component in multi-year cross-sectional metering designs. Results up to the previous year’s sample should in some way inform the current parameter and uncertainty estimates. This calls for a regression model or a Bayesian approach, both of which will be adopted below.

Once such a model has been constructed, survey sampling results and uncertainties should be combined with metering results and uncertainties to calculate the overall energy use (and savings) estimation, and overall reporting uncertainty. This will result in a more realistic uncertainty value being used for efficient study design. The American Society of Heating, Refrigeration, and Air-conditioning Engineers (ASHRAE’s) Guideline 14 on Measurement of Energy, Demand, and Water Savings [21] (henceforth referred to as G14) does provide a method for combining the three kinds of uncertainty mentioned above. However, such a holistic view of M&V uncertainty has not been adopted in the design of efficient M&V methods yet (the literature is discussed below). For example, the 90/10 criterion has previously been taken to apply to sampling uncertainty only, and not to the combined estimated savings figure, incorporating sampling, measurement, and modelling uncertainties. The proposed method integrates these uncertainty drivers in an optimizable manner. It also takes past metering and survey results into account when calculating the current energy use values and uncertainties. Incorporating past data in a mathematically sound yet informative manner has been a problem for M&V sampling design. Past samples in a longitudinal project contain information, both in their results and in their sample sizes. Since uncertainty in the parameter estimates decreases with more information, these past samples can be used to decrease uncertainty in the current estimates. The more information is available from past samples, the less information is needed from present and future samples to meet the uncertainty criteria for reporting. This means that smaller sample sizes may be specified for present and future points, if past data can be used. This increases statistical and financial efficiency. However, applying this information from past samples in a mathematically sound and time-sensitive manner is important. If this can be done, the method can then be used to forecast future uncertainties under different sampling regimes. An optimization algorithm can then be employed to select an efficient regime, thereby minimising M&V costs and increasing project feasibility.

A substantial body of literature about general M&V methods exists. A foundational mathematical description [22] has been provided, but most studies focus on regression methods for baseline determination, and not on sampling. For useful surveys of state-of-the-art regression methods, see Zhang et al. [23] and Granderson et al. [24]. Recently, Ke et al. have used Particle Swarm Optimization (PSO) to reduce modelling uncertainty in a regression problem [25] (although the use of PSO rather than matrix inversion for regression requires further motivation). Tehrani et al. have also used recursive Bayesian regression in a novel way for M&V adjusted baseline forecasting [26], and Shonder and Im [27] have also adopted a Bayesian approach.

Standard statistical sampling theory has been applied to M&V by internationally accepted guidelines. The required sample size is usually expressed in the form

$$n = \frac{CV^2 z^2}{p^2} \tag{1}$$

where p is the relative precision and z is the standard score. Therefore, 68 samples are needed for a 90% confidence interval ($z = 1.645$) at 10% precision, when the Coefficient of Variation CV = 0.5 [28]. The CV of a process provides a normalised measure of its standard deviation with respect to its mean. Therefore a process with a standard deviation of 50 and a mean of 100 has the same CV as a process with a standard deviation of two and a mean of four – their relative standard deviations are equal. Besides the G14, the two other leading international M&V guidelines, the International Performance Measurement and Verification Protocol (IPMVP) [1] and the Uniform Methods Project (UMP) [11], both recommend variations on (1), but do not consider longitudinal studies. The G14 [21] provides a method for aggregating results obtained over time based on Reddy and Claridge’s seminal work [29], but does not consider varying sample sizes, and does not quantify uncertainty as well as a Bayesian approach would [27,30]. It is well known that uncertainty quantification in standard regression can be a problem for anything but very simple cases, and methods such as bootstrapping and cross-validation are used for more complex cases [31,32]. A Bayesian approach proves to be a flexible and powerful alternative for efficient, exact uncertainty quantification.

2. Motivation

Standard sampling theory for non-longitudinal cases is well established – both for simple random, and stratified cases, and