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# Efficient longitudinal population survival survey sampling for the measurement and verification of lighting retrofit projects



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#### a r t i c l e i n f o

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## A B S T R A C T

A method is presented for reducing the required sample sizes for reporting energy savings with predetermined statistical accuracy in lighting retrofit measurement and verification projects, where the population of retrofitted luminaires is to be tracked over time. The method uses a Dynamic Generalised Linear Model with Bayesian forecasting to account for past survey sample sizes and survey results and forecast future population decay, while quantifying estimation uncertainty. A Genetic Algorithm is used to optimise multi-year sampling plans, and distributions are convolved using a new method of moments technique using the Mellin transform instead of a Monte Carlo simulation. Two cases studies are investigated: single population designs, and stratified population designs, where different kinds of lights are replaced in the same retrofit study. Results show significant cost reductions and increased statistical efficiency when using the proposed Bayesian framework.

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## **1. Introduction**

Measurement and verification (M&V) is the process by which savings from energy projects are independently and reliably quantified [\[1\].](#page--1-0) M&V is usually contractually required and is conducted by an independent third-party which audits the savings claimed by the Energy Services Company (ESCo) or contractor. However, measuring and verifying savings can be prohibitively expensive for some projects if savings are to be reported with the statistical accuracy required by most programmes. This is especially true for household Energy Efficiency (EE) projects [\[2\].](#page--1-0) To make M&V more cost-effective and increase the number and value of EE and Demand Side Management (DSM) projects, it is therefore necessary to devise monitoring and verification methods that adhere to the reporting accuracy requirements, but do so at low cost: so-called efficient designs [\[3\].](#page--1-0)

The cost of an M&V project is related to the uncertainty in the data, and the required statistical accuracy for reporting. There are three kinds of uncertainty that need to be mitigated for an M&V

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[http://dx.doi.org/10.1016/j.enbuild.2017.04.084](dx.doi.org/10.1016/j.enbuild.2017.04.084) 0378-7788/© 2017 Elsevier B.V. All rights reserved. savings estimate to be accurate. These are measurement uncertainty  $[4,5]$ , sampling uncertainty, and modelling uncertainty  $[6-8]$ . Of these, sampling uncertainty is often the dominant component [\[9,10\].](#page--1-0) Sampling uncertainty arises when the whole population of ECMs or facilities are not monitored. For example, when 100 000 Incandescent Lamp fixtures are retrofitted with Compact Fluorescent Lamps (CFLs) in a residential mass rollout programme, not all lamps can be tracked. In such cases it is necessary to take a sample of the population to determine the energy saved by the project. Often, the savings have to be tracked over a number of years. One study found that the cost of electricity saved decreases by 70% for studies where the monitoring period is increased from 1 to 3.9 years [\[11\].](#page--1-0) Therefore two factors need to be accounted for when reporting savings. The first is the amount of energy used by the average unit installed by the project. The second is the useful life of the unit, which determines the persistence of the savings. Over time the size of the original population shrinks according to its population survival curve, and so should the reported annual savings. Longitudinal M&V should monitor at least two values: the energy use of the equipment in a given year, and the proportion of original equipment that has survived to that year. In this study, we will focus on the latter: population survival. Although energy use can be measured with an energy meter, such meters cannot be used to





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measure population survival. Population survival should be determined through survey sampling, and the uncertainties associated with such sampling should be included in the overall M&V reporting uncertainty figure. In this paper we propose an efficient method that accounts for past sample sizes and population decay, quantifies uncertainty accurately, and provides a means of predicting future decay with reliably quantifiable uncertainty. This enables sampling planning and efficient survey designs.

This study is structured as follows. In Section 2, a brief review of the relevant literature is given. DGLMs are identified as an appropriate tool for longitudinal uncertainty quantification of population survival in M&V, although they have not been employed in M&V before. DGLMs allow for the application of previously developed [\[12\]](#page--1-0) autoregressive logistic population decay models to real-world datasets. As a preliminary step in Case Study 2, it was found that this parametrisation fits a wide range of CFL population decay data accurately. The sampling and optimisation model, assumptions, and lamp population survival theory is described in Section [3.](#page--1-0) It is shown how information such as past sample sizes and survey results can be incorporated into forecasts of future population decay in a mathematically rigorous way. A case study using a single CFL population and real-world data is presented in Section [4.](#page--1-0) A limitation in the use of Monte Carlo (MC) simulation for constraint determination in a Genetic Algorithm (GA) is illustrated, and an alternative analytical method is applied successfully. A novel penalty soft constraint function is also developed to increase the quality of the GA results. Section [5](#page--1-0) expands on the previous case study to include different strata (lamp types) in the same study – which, up to now, has only been possible under certain strict assumptions. Finally conclusions are drawn and recommendations made.

#### **2. Literature review**

### 2.1. Persistence

In a 1991 M&V guideline by the Oak Ridge National Laboratory, the authors noted that "Persistence is a genuine problem of undetermined scope. Its effects on cost-effectiveness, program planning, and resource reliability are clear. It is now time to address persistence in earnest"  $[13]$ . In a 2015 article  $[14]$  and a 2015 technical brief by the Lawrence Berkeley National Laboratory [\[15\]](#page--1-0) similar comments were made. This study addresses questions around characterising persistence curves and using them for efficient M&V study designs.

We consider technical persistence, or equipment lifetimes, only. The curves used may hold for overall persistence as well, but this is not proven. Laboratory tests and equipment lifetimes are not equivalent to actual persistence in the field  $[16]$ , and studies should also account for human- and market-related factors [\[17,18\],](#page--1-0) although the Uniform Methods Project (UMP) recommends that such factors are not taken into account for residential monitoring programmes [\[17\].](#page--1-0) For a foundational introduction to persistence study design, see Vine [\[19\],](#page--1-0) and for updated treatments, see Hoffman et al., Skumatz, and the UMP [\[15,16,20\].](#page--1-0) One engineering rather than statistical approach is to use technical degradation factors popular in the United States [\[15,21\].](#page--1-0) These are the lifetimes of the measures relative to the original equipment installed  $[22]$  – a single number, rather than curve characterisation or longitudinal studies as implemented below.

Since primary persistence research is expensive, most secondary sources are often used [\[20,16\].](#page--1-0) Primary research studies usually do not track populations, but try to provide a median measure life estimate [\[23,24\].](#page--1-0) Two notable exceptions are the Polish Efficient Lighting Project(PELP)[\[25\]](#page--1-0) and the Lighting Research Centre at Renssellaer Polytechnic Institute's Specifier Report on CFLs [\[26\].](#page--1-0) These datasets will be used. Another reason for selecting CFLs as the application technology for this study is that CFL retrofits are often used as M&V case studies [\[1,9,27,28\]](#page--1-0) as it is a well-studied technology with relatively simple principles.

Regarding the curve shapes, The United Nations Framework Convention on Climate Change (UNFCCC)'s Clean Development Mechanism (CDM) recommends a linear decay curve [\[29\].](#page--1-0) Logistic decay curves similar to those used in survival analysis have also been introduced [\[25,30,31\]](#page--1-0) and later improved upon [\[12\]](#page--1-0) to the form used in this paper to fit the datasets referred to above. Logistic curves are widely used in reliability engineering and applied to many technologies besides CFLs [\[32\],](#page--1-0) and will have wider applicability. More examples of linear and non-linear survival curve assumptions and study results for EE appliance models are listed by Young [\[33\].](#page--1-0)

Persistence monitoring requirements range from 3.9 years [\[11\]](#page--1-0) to 10 years for CDM lighting projects [\[34\].](#page--1-0) Pennsylvania and Texas require 15 years [\[15\].](#page--1-0) We will consider 10 and 12 year studies, as this reflects both regulatory requirements and realistic CFL lifetimes.

#### 2.2. Methods

Two methods are directly applicable to the problem at hand: Survival Analysis (SA) and regression. SA is used for time-to-event data, and can account for censoring (where exact failure times are unknown) as well as for measurement error. For an introduction, see Clark and Bradburn et al. [\[35–38\],](#page--1-0) and for an application to EE and DSM persistence studies, [\[24\].](#page--1-0) As with logistic regression, the focus of the method is on identifying the effect of covariates, and not on time-series forecasting, although such applications have been made [\[39\].](#page--1-0) Most SA models use the 'proportional hazards' assumption of fixed hazard or failure rates. This is not accurate for CFLs, although alternatives do exist and are mentioned below. SA is not used in this study, but is a promising approach for future persistence research.

The second approach is regression. Various methods exist in energy monitoring [40]. A suitable regression method should weigh points according to sample size, and account for the binomially distributed nature of the samples. It should also quantify uncertainty accurately. This was achieved in West et al.'s seminal work on Bayesian Forecasting and DGLMs [\[41,42\],](#page--1-0) building on McCoul-lagh and Nelder's GLM work [\[43\].](#page--1-0) Triantafyllopoulos [\[44\]](#page--1-0) provided a useful comparison of these and related methods such as particle filters and extended Kalman filters with posterior mode estimation. Gamerman and others have applied these models to survival analysis  $[45-47]$  and hierarchical models  $[48]$ . These models work with parametric distributions that do not describe the complexities of the energy savings calculations discussed in Section [4,](#page--1-0) but more research in this area is warranted. We have opted for a model similar on West, Harrison, and Migon's advertising awareness study [\[41\],](#page--1-0) which uses a DGLM with Bayesian forecasting to model binomial survey response data. This model uses the conjugate prior property of the beta-binomial distribution pair to incorporate information from past surveys into current estimates, even when those surveys found the population proportion to be higher than the current proportion due to decay. This is an implementation of Violette's proposal of using a Bayesian framework for longitudi-nal M&V studies [\[49\].](#page--1-0) However, this method goes beyond current M&V literature by then combining this beta-distributed population survival estimate with normally distributed energy data through a method of moments and the Johnson distribution. It also allows for stratified sampling designs with such distributions, which has also not been recorded in M&V literature, to our knowledge.

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