Exploring the commercial implications of measurement and verification choices in energy performance contracting using stochastic building simulation

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Abstract

Agreeing the level of energy savings that have been delivered is a fundamental part of an Energy Performance Contract. However, different measurement options use different measurement boundaries and may result in different answers. This is exacerbated in a retrofit of an existing building where little design information is available and reducing uncertainties through detailed surveys is generally cost and time prohibitive. This study uses probabilistic energy modelling to explore the implications of different measurement and verification strategies and concludes that some building users may find a performance guarantee offers them little protection. There is a need for greater transparency when making decisions about the most appropriate measurement and verification strategy.

Introduction

Energy efficiency is frequently cited as a fundamental component of the UK's strategy for achieving its carbon reduction commitments (see, for example, Department of Energy and Climate Change (2012)) but uptake of energy efficiency opportunities has generally lagged behind expectations, Hausman (1979), United States Congress Office of Technology Assessment (1992). Energy Performance Contracts (EnPCs) have been widely promoted as a mechanism for increasing uptake of energy efficiency investments by transferring the performance risk for the energy saving measure to the contractor responsible for its installation, European Commission (2014).

Measurement and verification of energy savings

The literature relating to EnPC is agreed on the importance of a robust arrangement for measuring and verifying (M&V) energy savings as a condition for a successful project. To date, the bulk of that literature has focused on the development of EnPC markets across a range of international settings: Jensen et al. (2013), Sarkar and Singh (2010), Urge-Vorsatz et al. (2007), Goldman et al. (2005), Vine (2005), Kavcic (2010), Patlitzianas et al. (2006), Marino et al. (2010), Bertoldi et al. (2006), Satchwell et al. (2010),

Goldman et al. (2002). The majority of commentators identify standardised M&V processes as a key market enabler (or, its absence as a key market barrier). Only two of these commentators take a slightly different view, with Jensen et al. (2013), placing a higher emphasis on trust in the context of Danish municipalities and Sarkar and Singh (2010) cautioning against over-complex M&V arrangements as a potential market barrier in developing countries. In addition, a variety of US based studies quoted in Kats et al. (1997) provide evidence of greater savings in projects with robust M&V arrangements.

The most commonly used approach for measuring and verifying savings is the International Performance Measurement and Verification Protocol (IPMVP) which grew out the US EnPC industry standards, Efficiency Valuation Organization (2012) with ten Donkelaar et al. (2013) reporting its use in just under 50% of 100 European projects surveyed. However, it is important to note that IPMVP does not present a detailed process for measuring savings but a framework that can be adapted to fit a wide range of circumstances. In particular, IPMVP contains 4 distinct options for measuring savings each with different measurement boundaries, since many ECMs may affect other building systems across these measurement boundaries, the total savings measured and thus guaranteed, may vary depending on the option selected.

For the EnPC market to achieve its aim of increasing energy efficiency investments, it is essential that clients have confidence in the level of guarantee offered under the contract since otherwise, the risks of investment will not be considered to be reduced. The potential for differing levels of savings depending on the measurement boundary selected leads to a risk that clients and contractors may have very different expectations of energy savings as a result of the investment in an EnPC with important consequences at an industry level as a result of a lack of confidence in future energy savings guarantees. To date, the literature has sought to explore the market level impacts of standardised M&V approaches as discussed above but has not considered the question of how a standardised M&V approach should be implemented
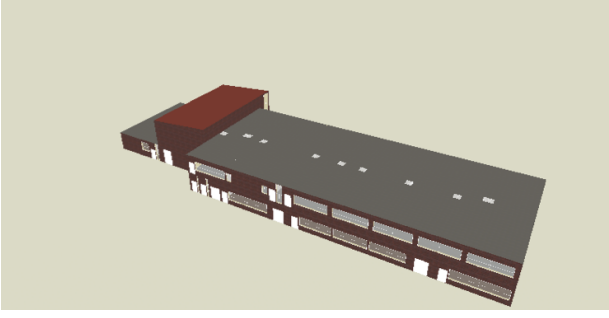
Figure 1: Archetypal UK primary school modelled in EnergyPlus

and the unintended effects which might arise. This study seeks to contribute to closing this gap by exploring the theoretical case of a lighting retrofit in an archetypal UK school to understand the consequences of alternative measurement options under IPMVP.

Simulation

A typical UK primary school (420 pupils aged between 4 and 11 years old, taught in classes of 30) was modelled in EnergyPlus. A fundamental complication of measurement and verification of energy savings is that since the energy savings are an absence of consumption they cannot be measured directly. It follows from this that establishing the baseline condition, the energy consumption which would have taken place if no energy efficiency measure had been installed is critical. Moreover, the literature on the energy performance gap has repeatedly demonstrated the difficulty in accurately calculating the energy performance of buildings in use, even where detailed design information is available. Where such information is no longer available and buildings may have been incrementally modified over the years with limited record keeping this situation is compounded. Whilst in theory, much of this missing information could be obtained from detailed surveys, in practice, the cost of obtaining this information and the time needed to do so mean that only limited survey work is undertaken. To capture this uncertainty surrounding the baseline condition of the archetypal school a stochastic approach is is required.

Screening

A literature review coupled with the lumped parameter approach proposed by Garcia Sanchez et al. (2014) was used to identify 91 variable input parameters, covering building fabric, systems, settings and occupant behaviour. Capturing the full range of variation over this large input space is time-prohibitive as the individual models are relatively time-consuming to run (3.5 minutes for parallel simulation of 8 primary school models). Consequently, a screening approach is necessary to select the most influential parameters which can be permuted in subsequent model runs with values for the un-influential parameters being

fixed. Global Sensitivity Analysis (GSA) considers variations across the full input space and is appropriate for a complex, non-linear model such as a building simulation model where interactions between input parameters are expected to be important, Saltelli et al. (2008). The GSA setting used in this context is a *factor fixing* setting. Variance based approaches, developed from the work of Ilya M. Sobol', represent the state of the art for GSA but come at high computational cost and are recommended for models with fewer than 20 input parameters Saltelli et al. (2008). Various studies, eg. Pannier et al. (2016), Sarrazin et al. (2016a) have shown that a repeated one-at-a-time analysis first proposed by Morris Morris (1991) provides results which are consistent with those calculated using Sobol' indices, Saltelli et al. (2006), for a factor fixing setting. This approach creates a series of sets of input parameters where each pair of sets differs in only one input parameter, consequently the variation in model output between the sets of input parameters is only due to the varied parameter. The Elementary Effect (EE) is the normalised difference in output resulting from the two sets of input parameters. A series of k+1 sets of input parameters is required to give 1 estimate of EE for each input parameter where k is the number of input parameters. Notation used throughout follows Campolongo et al. (2011).

$$EE_i = \left| \frac{y(x_i^{(u)} x_{\sim i}^{(u)}) - y(x_i^{(v)} x_{\sim i}^{(u)})}{(x_i^{(u)} - x_i^{(v)})} \right| \quad (1)$$

where:
EE_i is the elementary effect of the ith parameter
$y(x_i^{(u)} x_{\sim i}^{(u)}) - y(x_i^{(v)} x_{\sim i}^{(u)})$ is the difference in output resulting from input vectors u and v of the output parameters where parameter i is the parameter being held constant
$x_i^{(u)} - x_i^{(v)}$ is the difference in the input vectors

The procedure is repeated a number of times to give a number of estimates for EE for each parameter, in his original work, Morris used the mean and the standard deviation of the estimates for each parameter to characterise the sensitivity of the model output to changes in that parameter. Two key concerns regarding the original Morris Method have been addressed in more recent work. The first, the potential for the estimates of opposite sign to cancel each other out resulting in an influential factor being incorrectly classified as un-influential was addressed by taking the mean of the absolute values of measured variance, μ^* Campolongo and Saltelli (1997). Where

$$\mu_i* = \frac{1}{n} \sum_{j=1}^{n} \left| EE_i^j \right| \quad (2)$$

The second concern, that the coarse search pattern proposed with the original winding stairs approach

leads to inadequate coverage of the input space is addressed through the application of a radial sampling design Campolongo et al. (2011) this is the form used in equation 1.

Sampling the input space

Sobol' sequences were used to generate samples from the distribution U(0,1) for each parameter using the sobolset routine in Matlab based on Bratley and Fox (1988). Sobol' sequences were created to systematically fill the input space based on previously selected points and so are not strictly random numbers but have been demonstrated to provide better coverage of the input space than other sampling strategies such as random numbers or Latin Hypercube sampling, Homma and Saltelli (1996). The procedure set out in Campolongo et al. (2011) was used to generate 8280 samples for a radial sampling strategy. Each sample is mapped to the input space of the relevant parameter using the inverse of the cumulative probability density function (CDF) for that parameter since the CDF is by definition a continuous function between 0 and 1. However, this sampling strategy introduces instability in the outputs when the delta between input samples in the untransformed sample space is very small since this is the denominator used in equation (1), this causes a particular issue if the small delta occurs in the tail of the distribution since the delta in the input space after transformation may be significant. To reduce the effects of this instability, samples with an untransformed input delta ≤0.01 were excluded from the results.

The original formulation of the Morris Method uses a uniform distribution for all parameters which would tend to over-weight extreme values leading to type I errors where non-influential parameters are identified as influential. In the modified Morris Method used in this study, 3 types of distribution were used.

- Normal distributions were used for parameters where uncertainty is dominated by variation in physical characteristics and the spread is small relative to value. For example, boiler efficiencies, infiltration, lighting gains (post-retrofit)

- Triangular distributions were used for parameters where uncertainty was dominated by lack of knowledge of existing installed components or patterns of use and the spread is large relative to value since using a normal distribution would underweight extreme values and result in impossible values. For example: lighting gains (pre-retrofit), equipment gains, on/off times for lighting, equipment, occupancy or heating schedules

- Uniform distributions were used for parameters where information concerning the distribution of parameter values was not available or the parameter is a user-defined setting and all values are assumed to be equally likely. For example, domestic hot water loop outlet temperature.

Sarrazin et al. (2016b) highlight the need for robust techniques for testing for convergence of indicators over successive estimates and propose a semi-quantitative measure to do this:

$$S_i^{EET} = \frac{\mu_i*}{\max \mu_k*} \qquad (3)$$

Equation (3) expresses the input factor sensitivity as a fraction of the sensitivity for the most influential input factor, ensuring that it takes a value between 0 and 1. A threshold of T = 0.05 is proposed as the value for S_i^{EET} below which parameters are considered to have negligible influence. A rolling average was computed as each additional estimate was added to the sample and the difference between the upper and lower values of the 95% confidence interval computed. The screening result was considered to have converged when the maximum difference between the upper and lower limits was less than 0.05 for all parameters. The number of runs required to give good coverage of the input space was assumed to be the number of estimates required for convergence multiplied by the number of influential parameters. This result was then validated according to the procedure for screening validation set out by Sarrazin et al. (2016b). A subset of input factors X_0 is defined where

$$X_0 = \{x_i \text{ when } S_i < T\} \qquad (4)$$

and an additional set of model inputs is generated, $\{y \mid \overline{X_0}\}$ where the input parameters in X_0 are fixed while the remaining parameters are varied across their input space. Empirical Cumulative Distribution Functions (CDFs) are the calculated from the conditional and unconditional model outputs and a two-sample Kolmogorov-Smirnov (KS) statistic is used to estimate the discrepancy between the two sets of outputs.

Testing the effects of different measurement boundaries

The impact of different measurement boundaries was explored for a single ECM, a lighting upgrade comprising 2 parts: relamping, modelled as a reduction in lighting gains and lighting controls, modelled as a change in the lighting hours. Difficulties of data collection mean that very little data exists detailing lighting practices in UK schools Drosou et al. (2015). In Drosou et al. (2016) a study of lighting behaviour in 4 UK classrooms suggested that lights were used for most of the time that classrooms were in use. Since Drosou's data related to 2 secondary schools and the current study is based on a primary school where classrooms are in continuous use a simplified profile was used for the lighting schedules, with a single on and off time. A single occupancy schedule is used for the whole building which is considered to be appropriate for a primary school where occupancy density is high and most spaces will be in continuous

use. Diversity was introduced in the sample by treating the on and off times as variables sampled stochastically from symmetric triangular distributions. The lower bounds for on time and off time are based on a typical UK school day of approximately 9am to 3pm Qualifications and Curriculum Authority (2002). Upper bounds for on and off time are estimated based on potential for early morning cleaning schedules and evidence in Taajamo et al. (2014) of an average 51 hour working week for UK teachers. The resulting lighting schedules are shown in 2.
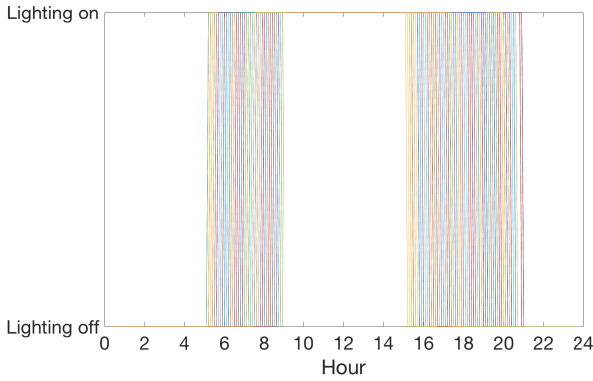
Figure 2: Lighting schedules prior to retrofit

Following retrofit, lighting hours are matched with occupancy hours to reflect the installation of occupancy sensors. Lighting fraction is introduced as a variable to allow for a proportion of lights to be switched off during the day. One of the very few sources of data for lighting use in schools is Drosou et al. (2016) where the authors report lights being used in a secondary school classroom for 60% of the school day in a building with occupancy sensing. This was taken as the lower bound for the lighting fraction as the space utilisation rate in primary schools is typically much higher than in secondary schools. Department for Education (0614).
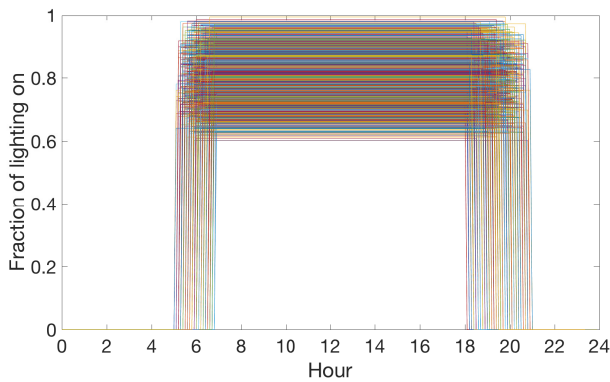

Figure 3: Lighting schedules post-retrofit

IPMVP, Efficiency Valuation Organization (2012) sets out 4 different approaches to measuring energy savings:

Table 1: lighting gain values

Pre-retrofit (symmetric triangular distribution)	Post-retrofit (normal distribution)
Classroom: 12-21 W/m²	4.4 W/m²(SD 0.22)
Office: 12-14 W/m²	5.4 W/m² (SD 0.27)
Hall: 12-13 W/m²	5.7 W/m² (SD 0.27)
Ancillary: 8 - 10 W/m²	3.1 W/m² (SD 0.16)

- Option A: Field measurements of specified key performance parameters and estimates for other parameters are used in engineering calculations. The measurement boundary is defined by the calculation undertaken and so may not encompass all aspects of the ECM

- Option B: Field measurements are taken of the energy use of the ECM-affected system. Measurements can be short term or continuous and would normally also cover the period prior to installation to establish a baseline level of consumption. The measurement boundary is the system considered. Other systems which might be affected are not included within the boundary.

- Option C: Energy use is measured at the whole or sub-facility level. Savings are calculated from analysis of the whole facility energy use pre and post ECM installation and regression analysis is typically used for routine adjustments.

- Option D: Savings are determined through a calibrated simulation model of the energy use of the whole facility or sub-facility. Measurement boundaries for options and C and D are conceptually the same and so option D is excluded from this analysis.

Savings were calculated pre and post-retrofit for using 3 different methods:

- Option A savings were calculated by assuming a baseline figure of 2000 annual lighting hours with the exception of offices which are assumed to have a baseline of 2500 annual lighting hours, Philips (2010). 2000 hours per annum equates to 10 hours of lighting per day (UK statutory school year is 190 days with 5 inservice days for teachers). Post retrofit, a 20% reduction in lighting hours is assumed as a conservative estimate based on manufacturers' claims, Guo et al. (2010). No allowance is made for uncertainty in these estimates to reflect standard practices identified in interviews undertaken by the authors as part of a broader study.

- Option B results are based on the lighting energy consumption calculated by Energyplus.

- Option C results are based on the whole facility electricity and gas consumption calculated by Energyplus.

Results and discussion

Screening and validation results

The relative impact of each parameter on electricity and gas consumption is shown in figures 4 and 5 respectively. In total, 90 estimates were obtained for the sensitivity of each of the 91 parameters and the impact of incrementally adding a new estimate at a different point in the input space is plotted on the x-axis. As successive estimates are added the results stabilise so that after approximately 50 estimates the separation between influential and non-influential parameters is unchanging. It can be seen that for many of the input parameters, there are particular settings which result in a large impact on the model outputs but that for most parameters, these settings occur infrequently with the result their impact is smoothed by the averaging process. The screening results thus indicate which parameters are most likely to be influential but this does not preclude the possibility of a particular setting resulting in a large impact on the outputs. It can be seen from figures 4 and 5 that the separation into influential and non-influential parameters is distinct.
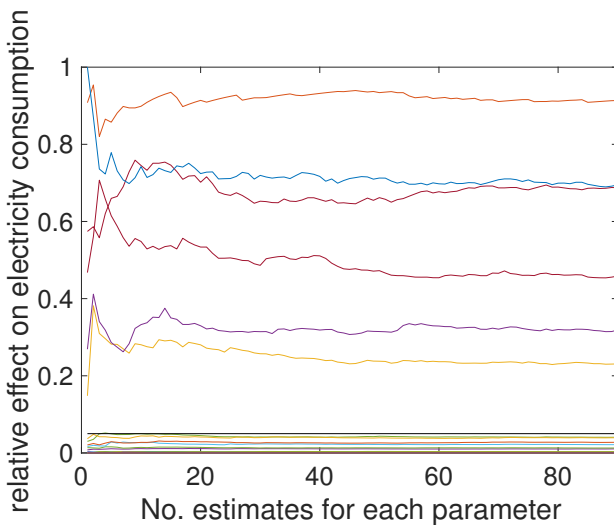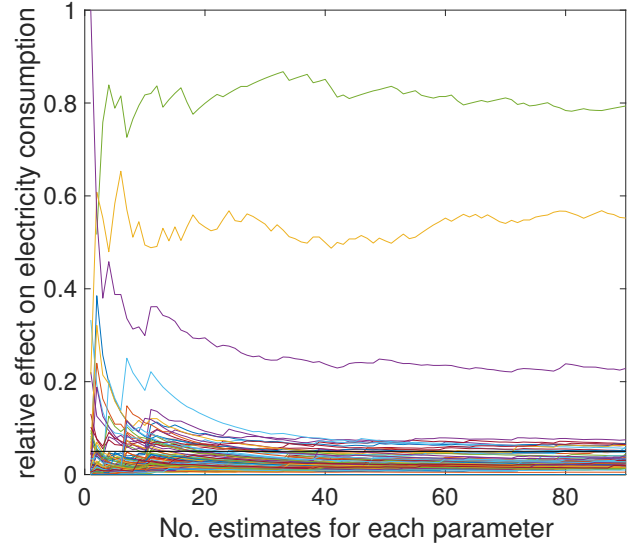

Figure 5: Successive estimates of relative impact of each parameter on gas consumption

6 parameters had a significant effect on electricity consumption ($S_i \geqslant 0.05$): classroom equipment gains, classroom lighting gains, general equipment on-time, general equipment off-time, general lighting on-time, general lighting off-time.

13 parameters had a significant effect on gas consumption ($S_i \geqslant 0.05$): intermittent heating set point, regular heating set point, intermittent heating set back band, regular heating set back band, general full occupancy end-time, general heating on-time, ventilation temperature, infiltration rate, boiler part load ratio, boiler efficiency, domestic hot water loop exit temperature, fibreboard thermal conductivity, classroom ventilation rate. Of these 13, 3 had a much greater effect: regular heating set point, ventilation temperature and infiltration rate.

The screening results were validated by comparing the cumulative distribution functions (CDFs) of the outputs from two sets of 950 runs (19 influential parameters x 50 estimates). In the first set all parameters are sampled from their input distributions using the sobol' sequence procedure detailed above, in the second set, the samples for the non-influential parameters were fixed at their mean values. Figures 6 and 7 respectively, indicate that the 2 CDFs for electricity consumption and for gas consumption are almost identical, indicating that virtually all of the variation in the outputs is explained by the influential variables and confirming the screening results.
[h]

Calculation of energy savings

As discussed earlier, post-retrofit lighting hours are linked to occupancy and so these were included in the list of influential parameters. An additional variable was included post-retrofit to model the percentage of lighting in use. 1200 runs were undertaken for the pre-retrofit condition with the non-influential param-
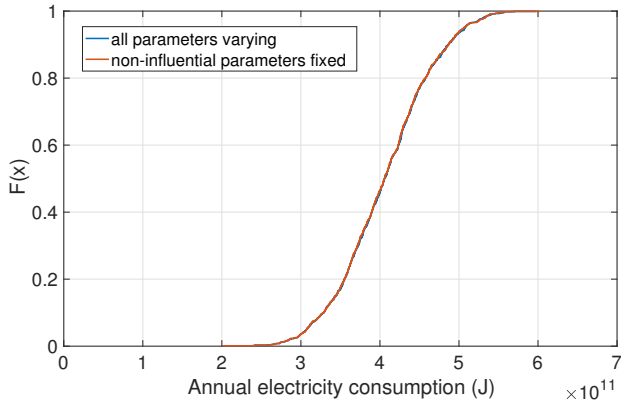

Figure 4: Successive estimates of relative impact of each parameter on electricity consumption

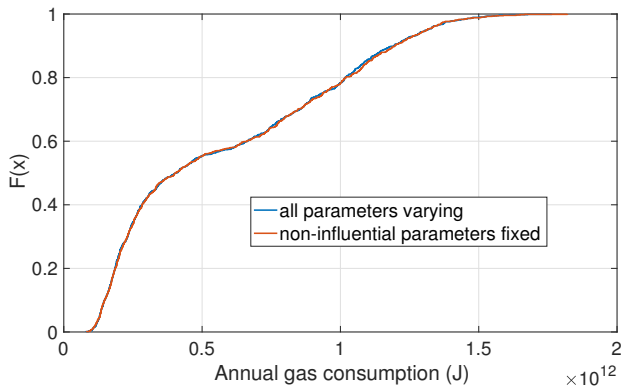Figure 6: *Screening validation for electricity consumption*

Figure 7: *Screening validation for gas consumption*

eters fixed at their mean value. Sample values for the parameters which were influential but unchanged by the lighting upgrade were reused in the post-retrofit condition.

Electricity savings

Figure 8 shows in blue the annual electricity savings calculated on a whole building basis and in red, the lighting energy saving, reflecting the option C and B savings calculations respectively. The annual electricity saving calculated using the option A method is 1.6×10^{11} J, this is shown as a broken line. These results indicate that there is good agreement between the option B and C calculations. It is also clear that the energy savings are closely linked to the number of lighting hours pre-retrofit. In the majority of the cases modelled here, lighting savings will be in excess of the option A predicted value. However, for the lower quartile of lighting users, savings will be lower than the value predicted as their original consumption was lower than estimated, in these cases, the performance guarantee offers no protection since the savings are deemed to have been met based on the engineering calculation. This is a concern since the inclusion of a performance guarantee typically adds cost to a procurement either directly or by limiting the range of potential suppliers to those who have the covenant strength to provide a guarantee. In these cases a client has incurred an additional cost, in excess of the underlying installation cost for a guarantee which offers them no protection.
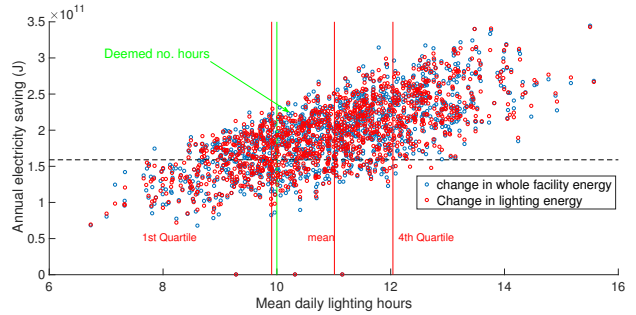

Figure 8: *Electricity savings*

Gas savings

Figure 9 shows the change in whole facility gas consumption following retrofit. In the majority of cases, the change is a negative one, i.e. more gas is consumed post-retrofit. The number of parameters affecting gas consumption is much greater than for electricity consumption and consequently the relationship between lighting hours and increased gas consumption is not as strong as for the change in electricity consumption. The cases where gas consumption decreases are linked to the increase in lighting hours post retrofit which occurs in a small number of cases. Both option A and option B ignore any impact on other building savings and the expected change in gas consumption in these cases is zero. However, as illustrated in figure 10, the increase in gas consumption is a significant proportion of the electricity saving. While the heat which was previously supplied by the original lights is more efficiently and cheaply supplied by the building′s heating system, for a client investing in a guaranteed electricity saving, an increase in the gas bill is likely to come as an unwelcome surprise.

Although these results might suggest that choosing a whole building approach to measuring and verifying energy savings is always in the clients interests, ESCOs may not be willing to accept the additional risks that this approach imposes on them. In particular, ESCOs are exposed to the wide ranging impacts of occupant behaviour which are outside their control. Better baseline information, particularly on lighting hours of use would reduce the risks for both parties significantly. The influential parameters identified through the parameter screening exercise provide a clear map of where to focus efforts to reduce uncertainty.

Conclusion

Lighting retrofit projects offer the opportunity to significantly reduce the electricity consumption of existing buildings. However, this will be partly offset by an increase in gas consumption and greater attention needs to be paid to the impact of measurement
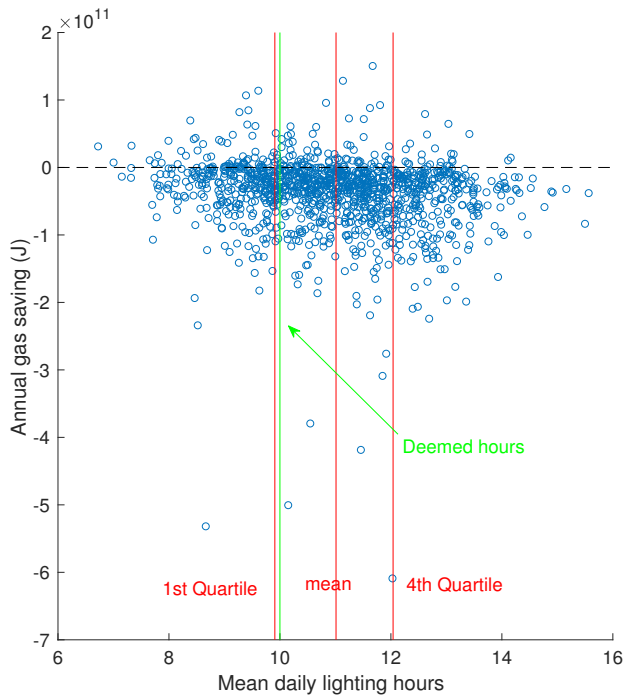
Figure 9: *Gas savings*

Figure 10: *Energy savings (or increases) as a result of retrofit*

boundaries and M&V strategy on the actual value of the guarantee for clients. The trade off between cost of monitoring and accuracy of results is likely to lead to a sizeable proportion of clients receiving lower than expected savings with no recourse under the guarantee. Energy Performance Contracts rely on a guarantee of savings to create an incentive for investment in energy efficiency but clients will see gas bills rise significantly even though the guaranteed saving has technically been achieved. This effect will be greater for clients with higher overall hours of lighting use. If this risk is not clearly explained to clients it is likely to lead to a loss of confidence in the concept of energy performance contracts as a whole.

Acknowledgement

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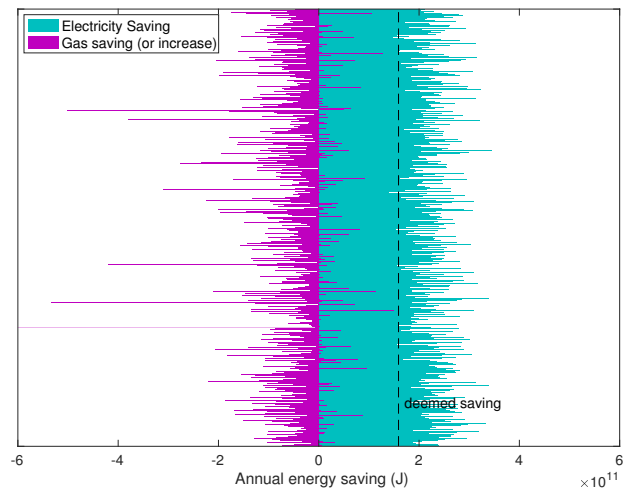Bratley, P. and B. L. Fox (1988). Algorithm 659: Implementing Sobol's quasirandom sequence genera-

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