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# Low-cost energy meter calibration method for measurement and verification

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## HIGHLIGHTS

- The effects of mismeasurement in energy monitoring are discussed.
- Simulation Extrapolation and Bayesian machine learning algorithms are applied.
- Even with low-precision meters as calibrators, acceptable accuracy is achieved.

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## ABSTRACT

Energy meters need to be calibrated for use in Measurement and Verification (M&V) projects. However, calibration can be prohibitively expensive and affect project feasibility negatively. This study presents a novel low-cost in-situ meter data calibration technique using a relatively low accuracy commercial energy meter as a calibrator. Calibration is achieved by combining two machine learning tools: the SIMulation EXtrapolation (SIMEX) Measurement Error Model and Bayesian regression. The model is trained or calibrated on half-hourly building energy data for 24 h. Measurements are then compared to the true values over the following months to verify the method. Results show that the hybrid method significantly improves parameter estimates and goodness of fit when compared to Ordinary Least Squares regression or standard SIMEX. This study also addresses the effect of mismeasurement in energy monitoring, and implements a powerful technique for mitigating the bias that arises because of it. Meters calibrated by the technique presented have adequate accuracy for most M&V applications, at a significantly lower cost.



## 1. Introduction

Measurement and Verification (M&V) is the process by which the savings from energy projects are independently quantified in a complete, conservative, consistent, transparent, and relevant manner [1]. M&V is usually mandatory if projects are to be eligible for incentives such as credits or rebates. In many cases, limits are placed on the uncertainty with which savings can be reported [2–4]. Following the International Standards Organization's Guide to the Expression of Uncertainty in Measurement (GUM) [5,6] this uncertainty is usually expressed as a relative precision at a given statistical confidence level.

The challenging aspect of M&V is that savings cannot be measured directly. Rather, a mathematical model of the energy systems' behaviour is created from measurements done prior to the intervention. This model may use covariates such as outside air temperature, occupancy, or production to characterise a facility's energy use. The model then predicts what the energy use *would have been* in the post-intervention period, had no intervention taken place. The difference between this predicted value and the actual measured energy use is the savings.

### 1.1. Definitions

Various technical and closely related terms are used in this paper. Before proceeding, their definitions are clarified. *Error* is the difference between the actual and the measured value. *Random* errors are distributed symmetrically around the mean, and usually

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follow a normal distribution. *Systemic* or non-random errors introduce bias. *Bias* "deprives a statistical result of representativeness by systematically distorting it" [7]. For example, biased data will consistently have a different mean to the true mean. Random errors usually do not have this effect, except in the case of *attenuation bias*, which will be discussed in Section 1.2.

*Uncertainty* is "the range or interval of doubt surrounding a measured or calculated value within which the true value is expected to fall with some degree of confidence" [3].

*Precision* relates to the "fineness of discrimination" [6] or "the closeness of agreement among repeated measurements of the same physical quantity" [3]. It is the uncertainty interval around a measured value, and should always be expressed with an associated statistical confidence. *Confidence* is a probability, whereas precision is a distance, or size of the error band. Confidence and precision together usually define the broader term accuracy, which is "the capability of an instrument to indicate the true value of a measured quantity" [3]. Note that the above definition of confidence, is popular although not technically correct [8,3,9,10] unless Bayesian methods are used.

By *calibration* we mean the process of comparing an instrument to a standard or reference (instrument) to characterise its errors and improve its accuracy. The range and kinds of values that should be compared are often codified in standards. *Disciplining* an instrument is a less complete calibration process where one only considers ranges and values expected to be encountered in a specific environment, and not the full range at which the instrument may be able to measure. Calibration is different from *qualification*, which ensures the quality of an instrument model range, because of its design and manufacturing process. For example, tests are done to ensure the stability of meter readings under different environmental conditions, specified by the IEC [11–14]. Although a specific meter may be qualified because it is part of a model range and never lose this qualification, it may drift out of calibration.

### 1.2. Uncertainty in M&V

During the M&V process, three forms of uncertainty arise: measurement uncertainty, sampling uncertainty, and modelling uncertainty [1,3]. These will be addressed in turn.

*Measurement uncertainty* refers to the difference between the actual and the measured values for a variable such as occupancy, outside air temperature, or energy. For projects where the interventions are spread over a large number of facilities, such as the residential mass rollout of energy efficient luminaires, it is not feasible to measure every home, and only a representative subset or sample is considered. This *sampling uncertainty* needs to be quantified [15–17]. *Modelling uncertainty* arises because mathematical models to not reflect reality perfectly [18–20]. Although some literature on sampling and modelling uncertainty exists [16,17,21] and a mathematical framework for M&V has been constructed [22], measurement uncertainty is often neglected. For example, the American Society of Heating, Refrigeration, and Air-Conditioning Engineers' (ASHRAE) Guideline 14 on Measurement of Energy, Demand, and Water Savings [3] assumes that data collected from US or Canadian National weather services are measured without error [3]. This may be true for the immediate vicinity of the weather station, but not necessarily for the facility at which M&V is done [23]. M&V measurement instruments include surveys, questionnaires, inspection reports, and various kinds of meters. In this study, we will focus on metering uncertainty and calibration, and propose a method for keeping this uncertainty within acceptable bounds, at low cost.

The ASHRAE Guideline [3] combines the three kinds of uncertainties into a single figure, and does give uncertainty values for common instruments. However, this guideline assumes normally- or t-distributed parameter estimates and does not consider the errors-in-variables effect, on which we will elaborate below. Other leading guidelines mention measurement error, but do not discuss its more detrimental effects [24–26]. A notable exception is the Uniform Methods Project [27,28], chapters 13 and 23. The Clean Development Mechanism (CDM) guidelines also use knock-down factors to account for measurement uncertainty [29].

It has been shown that assuming that measurement error is negligible is valid for cases where metering is done on a sample of a population with normal to high variance [30]. However, in cases where sampling uncertainty does not dominate measurement uncertainty, for example for single-facility studies or where all facilities are metered, the uncertainty in the meter data becomes significant in the overall uncertainty calculation. In such cases, measurement uncertainty may make a material difference to overall reporting uncertainty. Yet in all cases the reduction of measurement uncertainty through meter calibration is costly, not only because of laboratory fees, but also because of meter installation and removal costs.

A study of the present state of the art regarding measurement uncertainty in energy monitoring has been conducted [31], although it has not yet been published at the time of writing. One of the key findings relevant to this research is that the little-known errors-in-variables effect may be significant in some M&V cases. Briefly, conventional thinking is that bias in the measurements will bias the model, while zero-mean noise in the measurements will not bias the model. However, when unbiased noise in the measurement of the independent variables is present, it leads to biased ("attenuated") parameter estimates when these data are used for modelling [32,27,28,33]. This is the errors-in-variables effect. There are various methods of reducing this bias [34–36], and some of them will be implemented below.

### 1.3. Calibration in M&V

One way to circumvent or mitigate measurement uncertainty is to use accurate, calibrated meters. One then assumes that the measurement uncertainty is negligible. This is the approach taken by South Africa's 12L tax incentive programme [37], where meters are required to be calibrated by an accredited laboratory at fixed intervals. Other international programmes adopt similar approaches [38]. This is a sound principle from a regulatory point of view. It minimises the consumer's risk, that is, the risk of using an inaccurate meter. However, a significant opportunity cost is incurred because many projects are never implemented due to monitoring, laboratory, and plant shut-down costs. An example of this has been recorded for the CDM lighting retrofit project specifications [39,40]. Striking a balance between calibration costs and monitoring accuracy is, therefore, an important but non-trivial consideration for policy makers.

Our method also addresses a second calibration difficulty. The European Measurement Instrument Directive (MID) [41] requires that meters be calibrated in-situ, that is, in the environment in which they will be installed [42]. Besides regulatory compliance in European countries, a method capable of doing this is also convenient and practical. Various solutions have been proposed, from travelling laboratory-grade instruments with metrologists [42] to add-on calibrators [43]. However, these solutions entail high costs and specialised equipment. Because in-situ "calibration" does not test at all meter levels, but only at those experienced during the measurement period, we will sometimes refer to our method as "disciplining" or "verifying" the Unit Under Test (UUT) [44]. However, in mismeasurement statistics, the term "calibration" is often used to describe the procedure of correcting mismeasured data. For