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Assessment of linear emulators in lightweight Bayesian calibration of dynamic building energy models for parameter estimation and performance prediction

Qi Li*, Godfried Augenbroe, Jason Brown

School of Architecture, Georgia Institute of Technology, Atlanta, GA 30332, USA

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ABSTRACT

Calibration of building energy models is widely used in building energy audits and retrofit practices. Li et al. (2015) proposed a lightweight approach for the Bayesian calibration of dynamic building energy models, which alleviate the computation issues by the use of a linear regression emulator. As a further extension, this paper has the following contributions. First, it provides a brief literature review that motivates the original work. Second, it explained the detailed calibration methodology and its mathematical formulas, and in addition the prediction using meta-models. Third, it introduced new performance metrics for evaluating predictive distributions under uncertainty. Fourth, it used the standard Bayesian calibration method as the benchmark, assessed the capability of regression emulators of different complexity, and showed the comparison result in a case study. Compared to the standard Gaussian process emulator, the linear regression emulator including main and interaction effects is much simpler both in interpretation and implementation, calibrations are performed much more quickly, and the calibration performances are similar. This indicates a capability to perform fast risk-conscious calibration for most current retrofit practice where only monthly consumption and demand data from utility bills are available.

1. Introduction

Recent decades saw an increasing attention in pursuing energy efficient buildings, which has significantly benefited from implementing building energy modeling in design, operational management, life-cycle assessment and retrofit analyses. Compared to other types of models, dynamic building energy models are engineering based and can provide the most detailed prediction of building performance. This makes them very suitable for evaluating energy conservation measures (ECMs) and retrofit practice decision making.

However, considerable discrepancies exist between model prediction and field observation of building energy use in actual practices. Main causes include uncertainties in manufacturing, construction and building actual operation in reality. Assumptions, simplifications and approximations in modeling and simulation, also known as model inadequacy, are among the other main causes. In addition to improvement of model quality through detailed building audits, short-term testing, and energy monitoring, calibration of building energy models alleviates these discrepancies by adjusting model parameters through comparison between predictions and observations, such that the model outputs are close enough to the reality and model parameters remain realistic. In retrofit analyses, they will then be used to predict potential energy savings of ECMs, a solid basis for measure selection such that the expected benefits can be realized.

Li et al. [1] proposed a lightweight Bayesian calibration method that performs parameter estimation and performance prediction within a stochastic framework, and systemically handles multiple types of field observation to improve the results. Following a brief literature review, this paper will explain the proposed calibration and prediction methods in detailed mathematical formulas. After that a case study will be provided to demonstrate the method, as well as a thorough comparison of results from different linear regression emulators against the standard Bayesian calibration method under a variety of accuracy and efficiency metrics. Discussions and conclusion will be provided at the end.

2. Literature review

Current calibration methods and procedures in common use are summarized in Refs. [2,3]. In general, approaches to tuning

* Corresponding author.
E-mail address: qi.li@gatech.edu (Q. Li).

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dynamic models to field observations can be categorized into two groups. Manual calibration approaches mostly rely on iterative interventions by the modelers. The iteration usually requires special expertise and experience, and can be facilitated by several analytical tools, such as graphical comparisons [4] and signature analysis methods [5]. Some model simplification techniques are also commonly used in manual calibration practice [6–8]. However, manual approaches have drawbacks. First, special expertise and experience that required can only be acquired by real practice. In addition, in order to obtain a close match between model output and observation, these methods become time-consuming and labor-intensive due to much manual iteration in choosing and adjusting parameters.

Automated calibration approaches, on the other hand, can overcome these drawbacks by the use of mathematical and statistical techniques. Its general principle is to find the optimal value of parameters such that discrepancies between model prediction and measured data are minimized. This usually include several elements. First, an objective function needs to be specified to penalize the discrepancy, of which the most common function is coefficient of variance root mean square error (CV-RMSE) from ASHRAE Guideline 14 [9]. The objective function can also include terms that penalize unreasonable parameter values despite their capability of reducing discrepancy [10]. Second, exploration of the parameter space is performed to find the optimal values, either by parametric study in which the range of parameter values are specified based on experience [11], or by uncertainty analyses in which the possible parameter values are obtained through rigorous uncertainty quantification [12,13]. The computational cost of simulation can be reduced by fitting a statistical emulator to replace the physical model. Commonly used statistical emulators include Gaussian process [14], support vector regression with Gaussian kernels [15] and artificial neural networks [16,17]. However, most common automated calibration approaches, by providing only one or a small number of values, cannot fully consider uncertainties of model parameters and their propagation into predictions in a systematic way, which prevent them from considering potential risks of under-performing ECMs.

Bayesian inference has been applied widely in many scientific and engineering domains, and Bayesian calibration, as proposed by Kennedy and O'Hagan [18], combines information from different sources into an estimation of model parameters using Bayesian inference. It begins with modelers' knowledge and experience as prior beliefs for probability distributions of model parameters, and then maps them into a probability distribution of model output through building simulation. Given these output distributions, field observations are used via Bayes' rule to update those prior beliefs. This will provide posterior estimates of parameter probability distributions, such that by using these posterior estimates the behavior of building energy model is more closely aligned with reality. In addition, by introducing an additional mathematical term to account for the remaining discrepancies, Bayesian calibration explicitly considers the impact of model inadequacy and thus reduces the risk of over-fitting. All these features make the current Bayesian calibration technique to be a competitive method in calibration practice.

The application of the standard Bayesian calibration method in building simulation domain was first seen in Ref. [19], which calibrated a reduced order energy model that uses a quasi-steady-state formulation of heat balance equations and aggregated building parameters. It employed Gaussian process emulators for both the physical model and its model inadequacy. Prior distributions of model parameters came from uncertainty quantification techniques, and important parameters chosen by sensitivity analysis using Morris method [20] were calibrated against observation from utility bills. However, challenges remain in applying this standard Bayesian calibration method to dynamic building energy models. First, dynamic models typically have hundreds of uncertain parameters, which requires a huge-size sample of simulation results to fully reveal the response surface. Although the Gaussian process emulator, as used in the standard Bayesian calibration method, have exact fit with all the sample points, the computational effort increases drastically as the sample size increases and becomes prohibitively expensive for dynamic models. This motivates the attempt to use a simpler, less accurate but much faster emulator in the computation to improve overall efficiency while still obtaining satisfactory results. In addition, a full Bayesian analysis, i.e. estimating all of the parameters and coefficients in both the emulator and the model inadequacy term at the same time, adds to the computation demand with limited benefits. This issue can be addressed by a two-step approach where fitting emulator and estimating model parameters separately. Finally, commonly activities like detailed on-site visits, sub-metering, etc. provides valuable information for calibrating dynamic building models, and calibrations against multiple types of observations separately are susceptible to inconsistent and in accurate results of parameter values. This necessitates a systemic way to incorporate all the information in an automated calibration approach. All of the above reasons motivates the work in Ref. [1]. The following section will provide a detailed explanation of the methodology.

3. Methodology

3.1. Meta-model formulation

From a statistical perspective, the calibration problem can be formulated by the following meta-model, a classical representation from [18]:

$$y = \eta(x, t) + \delta(x) + \varepsilon_m \tag{1}$$

where y is standardized field observation, usually including the most common total energy consumption and peak demand for each month shown in monthly utility bills. y can also include indoor temperature, supply air flow rate, etc., that can be obtained from sub-metering or a building audit. Each type of output is standardized into [0, 1] by their separate minimum and maximum values to be obtained from experimental design and simulation; this ensures that all the types of observation are of the same magnitude and are considered equally important regardless of units. $\eta(x, t)$ is the output of dynamic simulation, represented as a function of model inputs x and model parameters t. For building energy models, model inputs mostly refer to the weather conditions. Their values for historical building consumption are commonly assumed to vary over time in a known manner, represented by the use of actual meteorology year (AMY) data files. Model inputs for this meta-model formulation also include output indicators, such that a single meta-model can yield outputs corresponding to different observations. Model parameters are building features that determine the consumption outputs given varying inputs. They include both physical parameters whose value remain relatively constant under considered time scope, like construction properties, and parameters that describe varying processes yet exhibit constant patterns, like average occupancy in a certain space. This meta-model also considers model inadequacy by including model error $\delta(x)$, assumed only depending on model inputs, and random observation error ε_m, assumed to follow a Gaussian distribution, i.e. $\varepsilon_m \sim \mathcal{N}\left(0, {\sigma_m}^2\right)$.

This meta-model relates field observation with simulation output through a mathematical formulation, and the calibration of building energy models within the retrofit context becomes: first, assuming the "true" value of unknown model parameters t is θ for the given historical observation, calibration aims to obtain a