Energy and Buildings 154 (2017) 343–355

Contents lists available at ScienceDirect

Energy and Buildings

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

Bayesian calibration of building energy models with large datasets

Adrian Chong [a,*], Khee Poh Lam [a,b], Matteo Pozzi [c], Junjing Yang [a]

[a] Department of Building, School of Design and Environment, National University of Singapore, 4 Architecture Drive, Singapore 117566, Singapore
[b] Center for Building Performance and Diagnostics, Carnegie Mellon University, 5000 Forbes Avenue, Pittsburgh, PA 15213, USA
[c] Civil and Environmental Engineering, Carnegie Mellon University, 5000 Forbes Avenue, Pittsburgh, PA 15213, USA

ARTICLE INFO

Article history:
Received 29 May 2017
Received in revised form 3 August 2017
Accepted 24 August 2017
Available online 31 August 2017

Keywords:
Building simulation
Bayesian calibration
Uncertainty analysis
Hamiltonian Monte Carlo
No-U-Turn Sampler

ABSTRACT

Bayesian calibration as proposed by Kennedy and O'Hagan [22] has been increasingly applied to building energy models due to its ability to account for the discrepancy between observed values and model predictions. However, its application has been limited to calibration using monthly aggregated data because it is computationally inefficient when the dataset is large. This study focuses on improvements to the current implementation of Bayesian calibration to building energy simulation. This is achieved by: (1) using information theory to select a representative subset of the entire dataset for the calibration, and (2) using a more effective Markov chain Monte Carlo (MCMC) algorithm, the No-U-Turn Sampler (NUTS), which is an extension of Hamiltonian Monte Carlo (HMC) to explore the posterior distribution. The calibrated model was assessed by evaluating both accuracy and convergence.

Application of the proposed method is demonstrated using two cases studies: (1) a TRNSYS model of a water-cooled chiller in a mixed-use building in Singapore, and (2) an EnergyPlus model of the cooling system of an office building in Pennsylvania, U.S.A. In both case studies, convergence was achieved for all parameters of the posterior distribution, with Gelman–Rubin statistics $\hat{R}$ within 1 ± 0.1. The coefficient of variation of the root mean squared error (CVRMSE) and normalized mean biased error (NMBE) were also within the thresholds set by ASHRAE Guideline 14 [1].

1. Introduction

BEM is increasingly being used for the analysis and prediction of building energy consumption, M&V and the evaluation of ECMs. To ensure the reliability and accuracy of an energy model, model calibration has been recognized as an integral component to the overall analysis [40]. Calibration can be viewed as the process of tuning model parameters until the simulation predictions match the observed values reasonably well. However, models are only as accurate as the inputs provided and detailed information is seldom available because it may be prohibitively expensive or even impossible to measure every tuning parameter of the model. Consequently, calibrating these models with limited data can often lead to over-parameterization and equifinality (i.e., the model parameters are not uniquely identifiable) [2]. Additionally, buildings are made up of complex systems interacting with one another and thus no single model is beyond dispute. Therefore, it is clear that there is a need for a calibration framework that is able to account for uncertainties in the modeling procedure [3]. Incorporating uncertainty would also allow risk to be better quantified. For instance, a risk-conscious decision-maker would prefer an ECM that yields a higher probability of guaranteed savings while a risk-taking decision-maker would prefer an ECM that yields the highest expected value [18].

Most calibration approaches that have been proposed are manual approaches that require the energy modeler to iteratively adjust individual parameters until a calibrated solution is achieved [9]. Westphal and Lamberts [48] used sensitivity analysis to first identify influential parameters, which were then adjusted to match simulation output to measured data. Through a case study, the approach was shown to be able to achieve a 1% difference between simulated annual electricity consumption and actual consumption. Using information from walk-through audits and end-use energy measurements, Pedrini et al. [35] carried out monthly calibrations and significantly reduced the difference between simulated annual electricity consumption and actual consumption. Tools such as graphical plots [40,28] and version control [39] have also been shown to be useful aids for guiding the calibration process. The main advantage of manual approaches is that model parameters are adjusted based on heuristics that are based on the expertise of an experienced modeler. However, these approaches are time consuming and labor intensive. They also rely heavily on the skills

* Corresponding author.
E-mail address: bdgczma@nus.edu.sg (A. Chong).

http://dx.doi.org/10.1016/j.enbuild.2017.08.069
0378-7788/

Nomenclature

Abbreviations

BEM	building energy model/modeling
COP	chiller coefficient of performance
CVRMSE	coefficient of variation of the root mean squared error
ECM	energy conservation measure
GP	Gaussian process
HMC	Hamiltonian Monte Carlo
IoT	Internet of things
KL	Kullback–Leibler
M&V	measurement and verification
MCMC	Markov chain Monte Carlo
NMBE	normalized mean biased error
NUTS	No-U-Turn Sampler
RWM	random walk metropolis

Physical quantities

$\dot{m}_{chw}$	chilled water mass flow rate [kg/h]
$\dot{Q}_{load}$	cooling coil load [W]
$\dot{V}_{chw}$	chilled water flow rate [m^3/s]
$\dot{V}_{frac}$	fraction of peak chilled water flow rate [–]
$T_{chw,in}$	chilled water inlet temperature [°C]
$T_{chw,set}$	chilled water setpoint temperature [°C]
$T_{cw,in}$	condenser water inlet temperature [°C]

Uppercase Roman letters

$\hat{R}$	Gelman–Rubin statistics
D	dataset
J	information or Kullback–Leibler divergence
L	number of leapfrog steps
N	$= n + m$
P	percentile
Q	sample quality
S	sampling schedule

Lowercase Roman letters

c	number of bins or categories after discretizing
m	number of simulation data
n	number of observed values
p	number of input factors
q	number of calibration parameters
r	number of attributes
s	starting sample size
t	calibration parameters
x	input factors
$y(x)$, y	observed output
z	$=[y_1, \ldots, y_n, \eta_1, \ldots, \eta_m]$

Greek letters

$\delta(x)$	discrepancy between simulation predictions and observed output
$\epsilon(x)$	observation errors
$\eta(x, t)$, η	simulator output
λ	variance hyperparameter of GP model
μ	mean value of elementary effects
μ^*	absolute mean value of elementary effects
ρ	$= \exp(-\beta/4)$
Σ	covariance matrix
σ	standard deviation
θ	uncertain parameters

Superscript

δ	discrepancy term
η	simulator
f	field data
S	simulation data
T	transpose of a matrix

Subscript

δ	discrepancy term
η	simulator
i, j, k	parameter or variable index
sub	subset of data
y	observations

Other symbols

ℓ^2	Euclidean distance
$\in$	a member of
$\mathbb{P}$	probability
$\mathbb{R}$	real numbers

and expertise of the modeler, making it harder to reproduce and thus restrict its widespread adoption. To overcome these drawbacks, there has been increasing research towards the development of analytical or mathematical techniques to assist the calibration process [9].

For example, Sun et al. [45] proposed a pattern-based automated calibration approach that uses programmed logic to identify calibration parameters that would be tuned to minimize biases between simulated and actual energy consumption. In their "autotune" project, Chaudhary et al. [6] proposed a methodology that leverages on large databases of simulation results and an evolutionary (meta-heuristic optimization) algorithm to automate the calibration process. Optimization approaches involve defining an objective function such as minimizing the mean squared difference between simulation predictions and measured data. To prevent unreasonable parameter values, the objective function can be augmented with penalty functions that penalizes solutions that differ significantly from the base-case [5].

Due to its ability to naturally incorporate uncertainties, Bayesian calibration is another automated approach that is quickly gaining interest. In particular, the formulation proposed by Kennedy and O'Hagan [22] has been increasing applied to BEM [18,41,17,27,7,30] because it explicitly quantifies uncertainties in calibration parameters, discrepancies between model predictions and observed values, as well as observation errors. With the emergence of IoT and as more sensors get deployed in buildings, there is an opportunity to constantly update and adjust model parameters through continuous calibration. A Bayesian approach provides a flexible framework for dynamically updating a BEM. As new data arrive, the old data is not discarded but instead assimilated to the new data through the use of priors [3]. In other words, the previous posterior density acts as the prior for the current calibration, thus providing a very systematic framework for the continuous calibration or updating of the energy model.

Despite several successful applications of Bayesian calibration to BEM, challenges remain in its widespread adoption. First, Bayesian calibration is typically carried out using RWM or Gibbs sampling. An inherent inefficiency of these algorithms can be attributed to their random walk behavior as the MCMC simulation can take a long time zig-zagging while moving through the target distribution [12]. Second, current application as described in [18] is computationally prohibitive with larger datasets. As a result, Bayesian calibration has been limited to monthly calibration data.

The objective of this paper is to address these challenges by proposing a systematic framework for the application of Kennedy