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A simultaneous calibration and parameter ranking method for building energy models

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HIGHLIGHTS

- A simultaneous calibration and parameter ranking method is developed.
- This method is accurate and computationally efficient compared to others.
- This method can help derive more reliable inputs for building energy modellers.
- This method can help identify priorities in retrofit for energy efficient buildings.

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ABSTRACT

The existing stock of buildings is a major contributor to energy-related carbon emissions. Significant savings in building energy consumption can be derived through retrofit. Building retrofits are typically guided by analyses through building energy simulation models. Due to the complexity of the physical characteristics of building systems and the lack of field measured data, modellers very often have to work with unknown or unmeasurable parameters either through approximation or with reference to the original design values. Since the values of these parameters usually fail to accurately represent the current conditions of existing buildings, it is important to calibrate these parameters before applying them in a building energy simulation model. In addition, it is also important to rank the input parameters according to their influence on building energy performance when identifying priorities for building retrofit. In this paper, a metamodel-based Bayesian method is proposed to simultaneously calibrate and rank input parameters to building energy simulation models. This proposed method implements both a model calibration procedure and parameter ranking procedure simultaneously when performing an analysis, which is much more efficient than applying these two procedures individually in separate model runs. As a further contribution, we extend the proposed method to one capable of handling large datasets. A case study is developed to demonstrate the accuracy and efficiency of the proposed method. Findings from the case study show that the calibrated parameters are usually different from the initially assumed values. In the context of the chosen existing building in Singapore, most of the considered parameters are key factors influencing building energy performance with cooling plant COP being the most important factor and natural exfiltration rate being the least important factor.

1. Introduction

Buildings account for nearly 40% of global energy consumption [1] and contribute to about 19% of energy-related carbon emissions [2]. Studies by the Intergovernmental Panel on Climate Change (IPCC) [3] suggest that building energy use and emissions may double or potentially triple by mid-century due to population growth, migration to cities, increased access to adequate housing, and other socioeconomic factors. Due to their long usage life, existing buildings contribute a large proportion of the total building stock. Improving energy performance of existing buildings through retrofit is key to reductions in building energy consumption and emissions. According to [3], building retrofits can derive about 50–90% energy savings in existing buildings worldwide.

Building energy simulation models have been widely used to provide guidance on retrofit. There are wide ranging simulation tools used

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Nomenclature

Abbreviations

APD	annual percentage difference
CI	confidence interval
COP	coefficient of performance
CVRMSE	coefficient of variation of root mean square error
GP	Gaussian process
GFA	gross floor area
HVAC	heating, ventilation and air conditioning
LHD	Latin hypercube design
$W/(m^2K)$	Watt per square meter Kelvin
W/m^2	Watt per square meter
m^2/person	square meter per person
m^3/h	cubic meter per hour

Symbols

z	real observations from existing building
y	simulated outputs from building energy model
$\boldsymbol{x}$	variable inputs
$\boldsymbol{\theta}$	calibration parameters
δ	discrepancy between existing building and building energy model
e	observation error
μ	Gaussian process mean, including μ_y for y and μ_δ for δ
σ^2	variance in the covariance function
R	correlation function
p	dimension of $\boldsymbol{x}$
q	dimension of $\boldsymbol{\theta}$
ϕ	decaying parameter in the correlation function
ξ	non-concerned unknown parameters
$f(\cdot)$	density function
$g(\cdot)$	prior density
$\boldsymbol{y}$	simulated building energy model data
$\boldsymbol{z}$	observed existing building data
$\boldsymbol{d}$	full data set $\{\boldsymbol{y}^T, \boldsymbol{z}^T\}$
$\boldsymbol{D}$	design inputs
$V_d(\theta)$	covariance function for $\boldsymbol{d}$
$\mathbf{0}$, $\mathbf{1}$	0 and 1 vectors/matrices
$\boldsymbol{I}$	identity matrix
$G(a,c)$	Gamma distribution with parameters a and c
χ	latent variable with indicators 0 and 1
Φ, X, Θ and Ξ	domains of ϕ_θ, χ, $\boldsymbol{\theta}$ and ξ respectively
$\mu_{z(x_0)\mid\boldsymbol{d}}$	predictive mean of existing building
$\sigma^2_{z(x_0)\mid\boldsymbol{d}}$	predictive variance of existing building
$\hat{V}_d(\theta)$	approximate covariance matrix for $\boldsymbol{d}$
h	inducing points

by scholars [4], such as DOE-2 [5], EnergyPlus [6], TRNSYS [7], and ESP-r [8]. Crawley and others [9] presents a comparison of the main features and capabilities of different tools and Connolly and others [10] provides a review of different computer tools. Building simulation tools, such as DOE-2 and EnergyPlus are capable of evaluating building energy performance by representing detailed physical characteristics of building systems. In addition to facilitating the design of energy efficient buildings, these tools are also gaining popularity in the post-construction phases of the building life cycle, which includes retrofit [11].

Building energy models are approximations of physical buildings. Due to the complexity of building systems and very often a lack of up-to-date operational data, modellers often have to assume estimated values for unknown or uncertain parameters, such as envelope thermal properties, occupancy schedules, hourly heating/cooling load, and receptacle power [12]. In order to achieve better representation of the existing buildings' physical and operational conditions, the estimated values of these parameters are critical to improving the accuracy of simulated building energy performance. In the literature, model calibration is among the popular approaches in estimating and/or adjusting the unknown parameters in building energy models so as to reduce the difference between the simulated and actual energy performance.

The importance of calibration has been demonstrated in many studies. Pan and others [13] considered envelope, internal loads and HVAC system among other parameters when applying calibration method to two commercial buildings. The results show significant improvements in the simulated electricity usage after calibration. Studies by Sun and Reddy [14], Sun and others [15], and Royapoor and Roskilly [16] also considered similar parameters when calibrating energy simulation models for office buildings. Their findings also suggest significant improvements in the accuracy of simulated results after calibration. The importance of calibration has thus attracted the development of building energy model calibration methods in the literature.

In general, the calibration methods can be categorized as manual and automatic calibrations [12]. Manual calibration can be implemented through various ways, such as through the characterisation of the physical and operational properties of existing buildings [17], graphical representation of building data or statistical indices [18], parameter reductions [19,20], and data disaggregation [21]. The manual calibration methods are usually dependent on expert knowledge and judgement, which can be prone to error. The automatic methods rely on computerised algorithms to assist in model calibration. One of the commonly used methods is to define an objective function [22] or a penalty function [23] followed by the application of an optimisation technique [14,24,25]. Another popular method is the Bayesian calibration method, which is capable of incorporating various uncertainties simultaneously in the calibration process [26,27].

The calibrated building energy models can be used to identify parameters influencing building energy performance. Some parameters may have a stronger influence on energy performance improvements than others. Thus, it is necessary to rank the influence of these parameters on building energy performance improvement so as to facilitate identifying priorities in building retrofit. Firth and others [28] show that heating demand temperature, length of daily heating period and external air temperature are among the key parameters influencing the accuracy of simulation results. The study by De Wilde and Tian [29] suggest that the window U value and heating efficiency of boilers could have a significant influence on the accuracy of simulation results. The study by Yang and others [30] found that chiller COP and occupant activity could also strongly influence the accuracy of building energy simulation results. Therefore, ranking these parameters taking into consideration the physical and operational conditions of buildings is important.

Various methods have been proposed to rank the influential parameters. The most common approach in ranking the parameters is sensitivity analysis, including local and global sensitivity analyses [31]. The local sensitivity analysis methods are usually implemented on a one-factor-at-a-time basis in which only one factor is changed each time while all other factors are kept constant. There are a number of methods for global sensitivity analysis, such as regression method [32–34], screening-based method [35,36], variance based method [37–39] and sampling method [40,41]. Although sensitivity analysis methods have been widely used to rank the parameters in building energy models, they usually require a large number of simulation runs, which can be time-consuming [42].

With increasingly large and complex building energy models, the