



Reduced-order modeling and simulated annealing optimization for efficient residential building utility bill calibration[☆]



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HIGHLIGHTS

- We use a procedure to evaluate residential building energy model calibration methods.
- We use building energy optimization software to make energy use predictions.
- An algorithm is used to calibrate an energy model to synthetic utility billing data.
- Simulations are replaced with response surface models to reduce computational cost.
- We compare methods in terms of computational cost and predicted savings accuracy.

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ABSTRACT

This simulation study applies the general framework described in BESTEST-EX for self-testing residential building energy model calibration methods. The National Renewable Energy Laboratory's BEopt/DOE-2.2 is used to evaluate an automated regression metamodeling-based calibration approach in the context of monthly synthetic utility data for a 1960s-era existing home in a cooling-dominated climate. The home's model inputs are assigned probability distributions representing uncertainty ranges, pseudo-random selections are made from the uncertainty ranges to define "explicit" input values, and synthetic utility billing data are generated using the explicit input values. A central composite design is used to develop response surface statistical models for the home's predicted energy use. Applying a gradient-based simulated annealing optimization algorithm to the statistical "metamodels", the calibration approach systematically adjusts values of the design variables and reduces disagreement between predicted energy use and synthetic utility billing data. Various retrofit measures are applied and used to assess accuracy of retrofit savings predictions resulting from using the calibration procedure. Substituting actual BEopt/DOE-2.2 model simulations with the statistical models reduces overall calibration procedure run-time while sacrificing only a limited degree of accuracy for retrofit savings predictions.

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1. Introduction

Building energy simulation programs are often used to model the thermal performance of commercial and residential buildings, and more specifically, to recommend energy efficiency upgrade packages and operational strategies for existing buildings. Due to uncertainties in building energy model inputs, accurate model

energy use predictions are not guaranteed.¹ Modelers often apply calibration procedures involving input value adjustments to pre-retrofit building energy models; the goal is to reconcile software predictions and measured energy uses. The general assumption is that calibrating the building energy model increases the accuracy of energy savings predictions for retrofit measures.

Understanding how uncertainties in simulation software energy use predictions may be reduced is important to recommending and achieving the most effective energy efficiency upgrade packages and operational strategies for buildings. The potential for reduction of energy consumption in buildings is maximized when the most impactful retrofit packages and operational strategies are considered and applied. Building model calibration may provide an

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¹ Input uncertainty is not the only known source of prediction error.

avenue for understanding and correcting the inaccuracies in building energy model inputs, thereby increasing energy savings prediction accuracy and confidence in the most potentially impactful retrofit packages and operational strategies.

Current model calibration methods range in complexity from manual calibration based on user judgment to automated calibration based on analytical, numerical, and statistical methods [1–10]. Due to the underdetermined nature of the calibration problem (i.e., there can be many combinations of input parameters that will result in good agreement with utility billing data), calibration solutions based on manual adjustments and user judgment may differ. Reddy and Maor [11] recognize the need for consistency in model calibration techniques, stating in ASHRAE 1051-RP that model calibration generally has been regarded as more of an art than a science. Some detailed guidelines, suitable for calibrating commercial building energy models using systematic and mathematical approaches, have been established in ASHRAE 1051-RP. However, these guidelines may not be cost-effective for residential building applications due to their computational expense. For example one of the suggested components, a refined grid search, can require numerous time-consuming model simulations.

This research presents and tests two automated calibration techniques based on the general guidelines set forth in ASHRAE 1051-RP, but adapted for residential building applications. Both methods involve using an automated, nonlinear simulated annealing optimization routine to iteratively predict energy use for combinations of input parameters and search for a calibration solution that minimizes an objective function [12]. The second of the two modifies the first to reduce the computational expense associated with costly building energy model simulations through substitution with more computationally efficient response surface models.

To test the accuracy tradeoffs in using these calibration techniques, a self-testing procedure described in Building Energy Simulation Test for Existing Homes (BESTEST-EX) [13] is employed. The test procedure describes a method for using a single software tool to compare reference, calibrated, and uncalibrated simulation results (see “Performing Calibration Tests Without Using Reference Programs” [Appendix B] of Judkoff et al. [14]). This study uses the software tool BEopt/DOE-2.2² and two calibration methods to assess energy savings prediction accuracy for retrofit measures. Section 2 describes the self-testing procedure.

Whereas individual BEopt/DOE-2.2 simulations take seconds to complete, optimizations requiring several thousand model simulations can become time consuming and very costly. Response surface models help to alleviate these costs since they are able to predict energy use by using minimally expensive reduced-order models requiring only simple arithmetic calculations. Section 3 describes the implementation of the calibration methods.

2. BESTEST-EX-based testing methodology

In this section, the approach used for evaluation of model calibration techniques is described. The approach is based on the self-testing procedure described in BESTEST-EX [13].

2.1. Define test house

One 1960'-era all-electric ranch-style home, partly-based³ on BESTEST-EX Case L200EX-P, is considered in the analysis. The

key pre-retrofit characteristics of the modeled house are given in Table 1.

2.2. Assign parameter ranges

To model uncertainty in audit-collected pre-retrofit data, probability distributions were assigned to building energy model input parameters. Inputs for which probability distributions were assigned are known as approximate inputs. Triangular probability distributions were used for this analysis, which are characterized by having greatest probability of selection at the “best-guess”, or nominal, value with linearly decreasing probability to zero at the input range extrema [13,16,11]. An asymmetric triangular probability distribution is shown in Fig. 1, where “Nominal” refers to the nominal (“best-guess”) value, “Min” the minimum value, and “Max” the maximum value.

The set of inputs with nominal values comprises the house’s “uncalibrated” model. Some ranges were specified based on those found in BESTEST-EX and limits set forth in BPI Standard 2400 [17]. Other ranges were estimated using engineering judgment. Ranges can be found in Appendix A of Robertson et al. [18].

2.3. Generate synthetic utility data

To obtain reference simulation results, explicit input values were first randomly selected from each of the triangular probability distributions. Explicit values were then substituted into the model’s corresponding BEopt building description file, and the file was simulated in BEopt/DOE-2.2 for a time period of one year using Typical Meteorological Year 3 (TMY3) weather data for Las Vegas, NV.

The set of $n = 12$ monthly total site electricity use predictions were extracted from the simulation output⁴ and became the “reference utility billing data” for model calibrations.

For this study, two utility billing data scenarios were considered by randomly generating multiple sets of reference utility billing data and then selecting two of the sets. One scenario had consistent overprediction (the uncalibrated model overpredicted reference billing data the entire season); this “overprediction” scenario was such that the uncalibrated model overpredicted the annual reference electricity consumption by 25.6%. The second scenario had compensating errors (the uncalibrated model overpredicted reference heating energy but underpredicted reference cooling energy); this “underprediction” scenario was such that the uncalibrated model underpredicted the annual reference electricity consumption by 4.7%. Investigating the two calibration methods in the context of multiple utility billing scenarios provides more information about the methods’ strengths and limitations.

2.4. Perform calibration

The next step of the self-testing procedure is to perform the input calibration procedures and recover “calibrated” models. In general, this involves applying adjustments to model input values until a desired level of agreement is achieved between simulation-predicted data and the reference utility data. Section 3 discusses the automated calibration procedures in detail.

2.5. Assess the benefit of calibration

Once the calibrated models have been recovered, various retrofit measures are applied to the uncalibrated, reference, and

² BEopt (Building Energy Optimization) is a residential building optimization tool developed by the National Renewable Energy Laboratory (NREL). See beopt.nrel.gov and Christensen et al. [15] for more information on BEopt.

³ Including heating and cooling systems (which were not considered in BESTEST-EX) allowed easier modeling with BEopt and permitted the testing of equipment-related retrofits.

⁴ This study considers only electric utility data since the modeled home consumes no other fuel type.

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