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HIGHLIGHTS

- A pattern-based automated calibration approach was developed.
- Includes logic linking parameter tuning with bias pattern identification.
- There are two types of bias patterns, Universal and Seasonal Bias.
- The model calibration approach is implemented in a web-based platform.
- The pattern-based calibration approach can be universally adopted.

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ABSTRACT

Building model calibration is critical in bringing simulated energy use closer to the actual consumption. This paper presents a novel, automated model calibration approach that uses logic linking parameter tuning with bias pattern recognition to overcome some of the disadvantages associated with traditional calibration processes. The pattern-based process contains four key steps: (1) running the original pre-calibrated energy model to obtain monthly simulated electricity and gas use; (2) establishing a pattern bias, either Universal or Seasonal Bias, by comparing load shape patterns of simulated and actual monthly energy use; (3) using programmed logic to select which parameter to tune first based on bias pattern, weather and input parameter interactions; and (4) automatically tuning the calibration parameters and checking the progress using pattern-fit criteria. The automated calibration algorithm was implemented in the Commercial Building Energy Saver, a web-based building energy retrofit analysis toolkit. The proof of success of the methodology was demonstrated using a case study of an office building located in San Francisco. The case study inputs included the monthly electricity bill, monthly gas bill, original building model and weather data with outputs resulting in a calibrated model that more closely matched that of the actual building energy use profile. The novelty of the developed calibration methodology lies in linking parameter tuning with the underlying logic associated with bias pattern identification. Although there are some limitations to this approach, the pattern-based automated calibration methodology can be universally adopted as an alternative to manual or hierarchical calibration approaches.

1. Introduction

The building industry is facing ambitious goals of aggressively reducing energy use. Currently, buildings consume more than one third of the world's total primary energy [1]. Measurement and simulation are two of the most common approaches used to monitor and evaluate building energy use [2,3]. Building performance simulation (BPS) provides (i) a quick and reliable assessment of building energy and environmental performance, supporting a building's life cycle including design, construction, operation and retrofit [4,5]; (ii) is often a more cost effective way to get detailed information about a building's energy use and, (iii) affords researchers the ability to easily assess the implications of different input variables on energy flows.

Despite the maturity of BPS, large discrepancies exist between predicted energy performance and the actual metered data [6–8]. This discrepancy can vary as much as a factor of 11 even in high-performance buildings that rely heavily on passive design, forcing architects to question the validity of simulation [9]. Some driving

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factors contributing to simulation uncertainty include (i) the intrinsic randomness of occupant behavior [10–12], (ii) climate impacts [13,14], (iii) operation and maintenance changes, (iv) alterations in the indoor environmental conditions, (v) internal heat gains, or (vi) building equipment [15]. This uncertainty undermines user confidence in model prediction and curtails the adoption of BPS tools during design, commissioning, operation and retrofit. To better ensure the validity of building simulation results, it is necessary that the existing models closely represent the actual behavior of the building. Building energy model calibration, the process of comparing building energy measurement data with simulated data, is one method to adjust input parameters to ensure a closer likeliness.

In general, model calibration is an over-parameterized process with an immense amount of inter-dependent input parameters that represent the complexity of building systems. Three critical reasons to conduct model calibration are to provide improved accuracy of building energy performance models [16], provide insights into a building's thermal or electric hourly load shapes [17], and better predict the potential energy savings of energy conservation measures [18]. The calibration target is to match the simulated energy consumption [11,19–21], indoor air temperature [6,22], operation conditions of HVAC equipment [18], and/or cooling/heating loads [6,18,23] to the actual measured data of the building, on a specific time scale. The calibration time scale usually depends on the calibration purpose and the accuracy level of available inputs. A smaller time scale calibration, such as hourly or even sub-hourly, is more difficult to achieve than a larger time scale such as monthly or annually. Usually more realistic inputs from measurements or audits are required to calibrate energy models at finer time scales. This study focuses on calibration method using the monthly building energy consumption data which are the most readily available.

A large amount of work has been done on the area of building energy model calibration. Pan et al. [11] presented a methodology for the calibration of building simulation models based on several re-evaluations of the internal loads to decrease uncertainty. Westphal and Lamberts [23] used sensitivity analysis to calibrate a building energy model using EnergyPlus. The technique first calibrates deterministic loads such as lighting and plug loads, then performs sensitivity analysis over input parameters, and finally adjusts input parameters which are more uncertain and have significant influences on energy consumption. The technique was applied to the modeling process of a public office building, and achieved about 1% difference between simulated and actual annual electric energy consumption. Pedrini et al. [19] conducted walk-through audits in 15 office buildings and monitored their hourly energy end uses to perform monthly calibrations. Following calibration the modeling uncertainties dropped from 130% to 10% [19]. Despite the effectiveness of calibration, many energy retrofit tools depend on manual iteration for calibration or do not provide the option to perform model calibration [24]. Therefore, research is needed in the area of expert or automated calibration and the development of new approaches that use logic, uncertainty and risk analysis, to advance the capabilities of building simulation [5].

Common techniques used to perform model calibration include [20,25]: (i) calibration based on manual, iterative and pragmatic intervention, (ii) calibration based on a suite of informative graphical comparative displays, (iii) calibration based on special tests and analytical procedures, and (iv) analytical/mathematical methods of calibration. These approaches can more broadly be categorized as manual and automated techniques [26]. Manual calibration is based on the iterative and pragmatic intervention of the modeler. It involves tuning or refining initial input parameters in a heuristic manner, relying heavily on the experience and expertise of the modeler [27,28]. Manual calibration utilizes building characteristics data from audits, energy use and zone condition monitoring, or active functional testing, to gain an intimate knowledge of the physical and operational characteristics of the building [19,21,29]. Graphical techniques have been widely used in manual calibration to visually show the differences between measured and computed results, following manual parameter tuning [28,30–33]. The main advantage of the manual calibration is that it combines human intelligence, expertise and experience into a trial-and-error process often making the calibrated model more reliable and closer to the actual building [33–35]. However, since manual calibration requires hand-operated skill, it is a time consuming and costly process. Also, poor data quality, due to inadequate maintenance and sensor calibration, may result in low resolution information for attuning models. Moreover, the credibility of the process can be questioned because calibrated models often depend upon modeler expertise and subjectivity. Lastly, the manual approach cannot be easily scaled up as every model may be different (e.g. building type, characteristics, operations, climate, etc.) and dependent upon the modeler for completion.

Unlike manual calibration, automated calibration commonly relies on mathematical and statistical techniques, which usually utilize some form of optimization function to reduce the difference between measured and simulated data. An objective function may be used to set a target of minimization, for example, the mean square error between measure and simulated data. Conversely, a penalty function may also be employed to reduce the likelihood of deviating too far from the base-case [36–38]. Sanyal and New [39] proposed a methodology in their "auto-tune" project, leveraging supercomputing, large databases of simulations, and machine learning to implement automatic model calibration. The state-of-the-art automated calibration is more akin to solving a problem of multi-objective optimization, which is more mathematical-based rather than physical-based [38,40,41]. In other words, the calibrated simulation results are able to match well numerically with the measured data, but may not necessarily match the actual building physically. At the same time, current automated calibration requires large amounts of computation bringing the need of supercomputing to complete the calibration process in an acceptable time scale. This restricts the widely spread and adoption of automated calibration.

In the current literature, there is no single methodology generally adopted for calibration of building energy models [42,43]. The lack of formal methodology can result in findings that are "highly dependent on the personal judgment of the analyst doing the calibration" [25]. Additionally, model calibration is often dependent upon the various uncertainties associated with building simulations and specific idiosyncrasies of a building system configuration [44,45]. To address these shortcomings, this paper presents a novel methodology for conducting automated model calibration based on pattern recognition. The approach combines the strengths of both manual and automated calibration with the aim that the pattern-based approach can be widely used. The paper provides insights into the following questions:

(1) Can an automated model calibration process be developed to encompass more intelligence than just using mathematical optimization based methods? For example, can the automatic tuning of parameters be developed by examining patterns of comparisons between simulated and measured energy use?
(2) If the automated model calibration can be accomplished using comparison patterns, how would these patterns be identified?
(3) What would be the logic flow of this automated model calibration and how would the methodology work?

2. Methods

An automated calibration process was developed by comparing a sequence of differences between monthly electricity and gas consumption profiles generated from building simulations versus actual utility data. The novelty of this methodology relies on the auto-identification of patterns and the logic in selecting to-be-tuned parameters according to the specific patterns. One objective in the development of this pattern based calibration approach was to generate a calibrated model using minimal inputs. The only inputs required for the building model calibration process were the monthly electricity bill, monthly natural gas bill, weather data and the to-be-calibrated model. The process begins using the input information and relies on parameter auto-tuning that iteratively alleviates discrepancies between the simulated and actual energy use profiles. The selection of the parameter and the parameter range for tuning was dependent upon the specific characteristics of the pattern mismatch. This iterative process of shape identification, parameter selection and parameter tuning occurs until pattern convergence within a specified tolerance. Fig. 1 shows an overview of the general logic of the automated calibration process.

2.1. Establishing a pattern bias

Generic pattern biases are identified and used at the start of each calibration process. A pattern bias, in this case, refers to the difference between simulated results and the measured data. The two distinctly different generic biases are the Universal Bias and the Seasonal Bias. The Universal Bias theoretically occurs when the monthly electricity or natural gas bill is consistently higher or lower than simulated results (Fig. 2). Due to the fact that simulations often can't capture all extraneous factors, that can cause unexpected fluctuations in patterns, a tolerance level of 10% was added to the definition of the Universal Bias. In other words, a pattern will be identified a Universal Bias pattern if the simulated data was consistently higher or lower than the measured data for 11 or more months. A factor which could lead to a positive Universal Bias in the monthly electricity consumption, regardless of climate conditions, would be an increase in the lighting power density. Additionally, an increase in the cooling COP can lead to a negative Universal Bias in the monthly electricity consumption when cooling is supplied year round.

A Seasonal Bias has the common characteristics of the monthly electricity or natural gas bill being partially higher and lower than simulated results, throughout the year. This more complicated pattern recognition results in multiple variations and shapes, making the algorithm for identification more complex. The three most common Seasonal Bias shapes were when: (i) simulation results were partially higher and lower than the actual profiles and contained interception points, (ii) miss-matched peaks occurred or (iii) miss-matched tails occurred (Fig. 3). The seasonal variation of electricity usage is mainly affected by cooling and occasionally by heating (or reheat). Meanwhile, the seasonal variation of gas is mainly affected by heating or reheating. Therefore, the Seasonal Bias commonly occurs in climate conditions that have distinct seasons. For example, an increase in the outdoor air flow rate can lead to a positive Seasonal Bias in the hot summer as well as negative Seasonal Bias in the cold winter for monthly electricity consumption. Such conditions are illustrated in Fig. 3(a), where monthly electricity bill in the summer (May to October) is higher than simulated results while lower during the winter (November to March).

Depending on different climate types, either a Universal Bias pattern or a Seasonal Bias pattern can appear, when tuning the same parameter. For example, tuning the building's cooling set point with a slight increase, can lead to a negative Universal Bias for the monthly electricity consumption of a building in a hot all year round climate, but often results in a Seasonal Bias for climate types with distinct seasons. Regardless of how parameters are changed the resulting profiles will always reflect a generic Universal or Seasonal Bias pattern.

2.2. Selection of to-be-tuned parameters

The automated calibration approach uses the intelligence of the generic patterns to determine which parameters to tune. This is a different approach than most conventional techniques that only use a hierarchical process that often depends on a predefined classification schema [44]. However, both processes use an initial predefined inclusive set of parameters to be selected for adjustment. The question becomes which parameters out of the many different options should be selected as potential parameters to-be-tuned.

A parameter selection process to list all possible parameters for potential selection during auto-tuning, was determined through a sensitivity analysis using EnergyPlus and coupled with engineering judgement. This technique broadly followed O'Neill et al. [46] who identified which calibration parameters would influence the calibration process the most using a Department of Energy (DOE) reference medium office building as a baseline model. In the sensitivity analysis, a medium-size, three story, rectangular office building (4982 m^2 conditioned area), with 5-zones per floor (one central zone and four perimeter zones) was simulated [47]. By tuning different input parameters using EnergyPlus version 8.0, for different climate types, and with different heating/cooling systems, the priority list of parameter selection was established. The parameters that exhibited the widest uncertainty following minor modifications were selected. This trait indicated that the original input values may have an associated higher uncertainty and perhaps be more likely in need of tweaking, which can be done through the calibration process. Table 1 shows the general list of 17 changeable parameters. However, depending on the bias patterns and input parameters, not all of the to-be-tuned parameters are tuned. The specific parameter selection and tuning is unique for each building calibration.

2.3. Establishing the logic behind which parameter to tune first

To establish logics behind which parameter to tune first, guidelines on the impact of climate conditions were established. Cooling and heating was targeted primarily because (i) it represents a significant portion of electricity and natural gas consumption for most small and medium commercial buildings, and (ii) more broadly the weather considerably affects thermal loads and thus energy

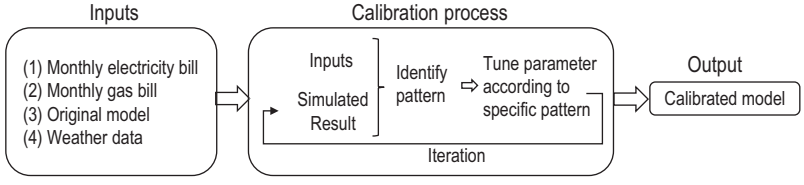

Fig. 1. The inputs, calibration process and outputs for the automatic calibration.

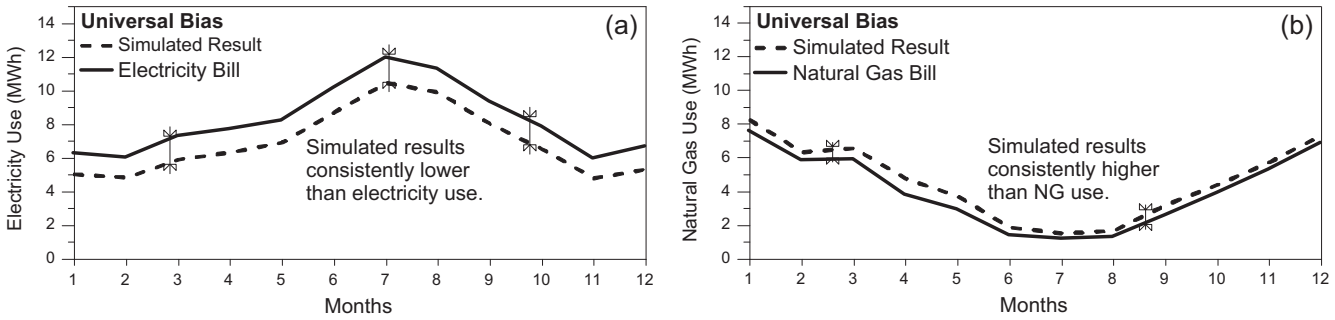

Fig. 2. Examples of a Universal Bias existing between simulated vs. actual profiles for (a) electricity use and (b) natural gas use.

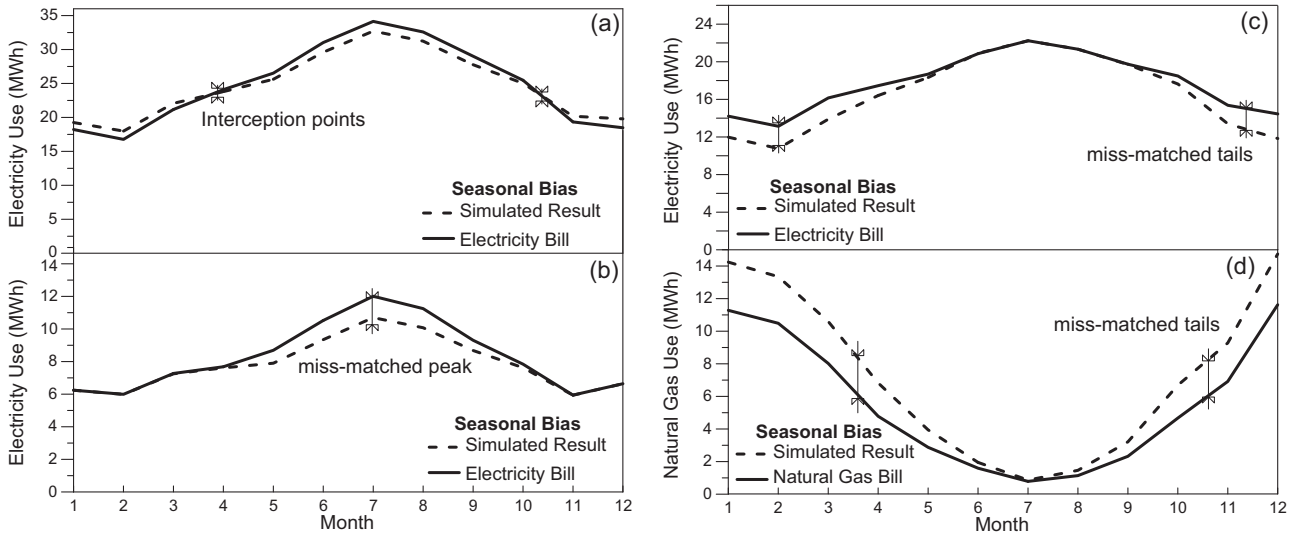

Fig. 3. Examples of the three most common Seasonal Bias shapes (a) being partially higher and lower than simulated results with interception points, (b) miss-matched peak, (c) miss-matched tails for an electricity profile and (d) the miss-matched tails for a natural gas profile.

Table 1
List of parameters that potentially can be adjusted during the calibration process.

Category	Parameters
Internal loads	Occupant density Lighting power density Electric equipment power density Outdoor air flow rate Infiltration rate
HVAC system	Cooling equipment efficiency Heating equipment efficiency Fan efficiency Cooling set point (schedule) Heating set point (schedule) Economizer status
Construction	Window *U*-value Window SHGC
Schedules	HVAC operation schedule Lighting schedule Electric equipment schedule

performance [1]. Therefore, the weather input data was relied upon for developing the underlying algorithm for the initial selection of parameters.

To establish logics behind individual parameter selection the severity of the climate was characterized in terms of heating degree-day (HDD) or cooling degree-day (CDD) [48]. To define cooling-dominant and heating-dominant months, the indices of CDD10 (cooling degree-day base 10 °C) and HDD18 (heating degree-day base 18 °C) from ASHRAE Standard 90.1 [49] were utilized. Therefore, a day can be considered as cooling-dominant if the mean temperature was higher than 14 °C (the average of 10 °C and 18 °C), or heating-dominant on the contrary. Furthermore, a day can be considered cooling-only if the daily mean temperature was higher than 18 °C, or heating-only if the daily mean temperature was lower than 10 °C. When the CDD10s of a month were greater than 120 $\{(14-10)*30=120\}$, it was defined as a cooling-dominant month; when the CDD10s of a month were greater than 240 $\{(18-10)*30=240\}$, it was defined as a cooling-only month. Likewise, a month was defined as a heating-dominant month if its HDD18s were bigger than 120 $\{(18-14)*30=120\}$, and a heating-only month if the HDD18s were greater than 240 $\{(18-10)*30=240\}$. These definitions take 30 as the average number of days in a month. From this, five climate types were defined as (1) *hot all year round*, (2) *cold all year round*, (3) *hot summer & cool winter*, (4) *warm summer & cold winter* and (5) *mild*. To clarify, if cooling was supplied throughout the year, which means that all months were cooling-dominant, the climate type was defined as *hot all year round*. The corollary was true for *cold all year round*. If not all of the months were cooling-dominant or heating-dominant and the number of cooling-only months was bigger than that of heating-only months, the climate type was defined as *hot summer & cool winter*. If not all of the months were cooling-dominant or heating-dominant, and the

number of heating-only months was greater than cooling-only months, the climate type was defined as *warm summer & cold winter*. If not all of the months were cooling or heating dominant, and there were no cooling-only months or heating-only months, meaning the monthly CDD10s and HDD18s were no greater than $(18-10)*30=240$, the climate type was defined as *mild*. Table 2 shows a summary of the climate type definitions.

After defining seasonal behavior, the next steps were to categorize the parameters that were the most frequently influenced by an associated climate type. For example, for the climate type *Hot all year round*, changing the cooling-related parameters (e.g. cooling efficiency, cooling set point, HVAC schedule) usually caused a Universal Bias in the monthly electricity consumption. Likewise, in a heating-dominant climate, *cold all year round*, changing the heating-related parameters (e.g. heating efficiency, heating set point, HVAC schedule) usually caused a Universal Bias in the monthly gas consumption.

A Seasonal Bias almost always existed in climate zones with more distinct seasons. Considering that cooling was the main source of electricity consumption, a positive or negative Seasonal Bias in the monthly electricity consumption was identified when the bias in cooling-dominant months minus the bias in heating-dominant months was greater or less than zero. Likewise, a positive or negative Seasonal Bias in monthly gas consumption was identified when the bias in heating-dominant months minus the bias in the cooling-dominant months was greater or less than zero.

To simplify the algorithm, the fuel for the heating source was fixed as natural gas, with three possible reheat types: reheat with gas, reheat with electricity and no reheat. These parameters influence the energy consumption of reheat. For example, in a *hot summer & cool winter* climate, if reheat was supplied by gas, changing the heating set point will cause a Seasonal Bias in the monthly gas consumption (no influence on electricity); if reheating was supplied with electricity, changing the heating set point will cause a Seasonal Bias in both the monthly gas and electricity consumption.

For a certain climate type paired with a reheat type, a change in a single parameter leads to a specific combination of pattern changes in the monthly electricity and gas consumption. For example, in a *warm summer & cold winter* climate and *reheat with gas* mode, decreasing the lighting power density will result in a negative Universal Bias in monthly electricity consumption together with a positive Seasonal Bias in monthly gas consumption.

Following this general logic, the parameter selection process was developed. The climate type is established upfront by computing CDD10 and HDD18 from the annual weather file. The process starts by using the generic pattern bias recognition. The most straightforward pattern identification is the recognition of the Universal Bias pattern. First the algorithm identifies if a Universal Bias exists. If no Universal Bias is identified, the pattern recognition moves on to recognize a Seasonal Bias. Depending upon the combination of applicable inputs, a limited number of possible parameters are identified from the possible 17 to-be-tuned parameters. This parameter field is narrowed based on the combination of pattern identification, original inputs and weather logic. Once the parameter is selected to be tuned, the question becomes how much to tune it.

Table 2
Summary of the defined climate types used to establish the logic behind parameter selection.

Climate type name	Monthly cooling degree days (CDD10)	Monthly heating degree days (HDD18)
Hot all year round	>120 for almost every month	n.a.
Cold all year round	n.a.	>120 for almost every month
Hot summer & cool winter	>240	# of cooling-only months > # of heating-only months
Warm summer & cold winter	# of heating-only months > # of cooling-only months	>240
Mild	<240	<240

2.4. Tuning calibration parameters

For automatic tuning, the original input parameters were allowed to be tuned using an upper and lower bound of ±30% from the original input values. From the original value to the upper or lower limit, the selected parameter was assigned a series of values for its tuning direction. This generates a series of sub-models to compare simulation results with the utility bill profile. The sub-model with the minimum Normalized Mean Bias Error (NMBE) and Coefficient of Variation of the Root Mean Square Error (CVRMSE) is chosen for the next calibration step. The NMBE and CVRMSE follows ASHRAE Guideline 14 [50] and are determined by comparing predicted results ($\hat{y}$) with the measured data used for calibration (y_i) and where (n) represents the number of months and ($\bar{y}$) is the average. NMBE and CVRMSE are calculated using Eqs. (1) and (2), respectively:

$$\mathrm{NMBE}=\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)}{n\times\bar{y}}\times 100 \tag{1}$$

$$\mathrm{CVRMSE}=100\times\left[\sum_{i=1}^{n}(y_i-\hat{y}_i)^2/n\right]^{1/2}\Big/\bar{y} \tag{2}$$

A value of 5% for the NMBE and 15% for the CVRMSE was used as the threshold level. In other words, if the NMBE and CVRMSE of the simulation results reach or are lower than 5% and 15%, the model calibration stops and the model is considered calibrated.

2.5. The automatic calibration process

The calibration process goes through a series of iterative steps prior to arriving at a calibrated model. The automated calibration starts with two comparison patterns: (1) the monthly electricity bill compared with simulated monthly electricity consumption and, (2) monthly natural gas bill compared with simulated monthly gas consumption. From this the bias types (Universal or Seasonal) of the two patterns are identified. For different bias types, weather conditions and reheat types, the tuning parameter rules are applied. A single parameter (from the list of 17) is selected, tuned and the building simulation regenerates new electricity and gas profiles. Following the re-simulation, the ASHRAE Guideline 14 [49] criteria are assessed and the process will repeat with another iteration if the criteria is not met.

To automate this iteration process four main programming modules were developed including: (1) the UBIden (Identification of Universal Bias), (2) UBElim (Elimination of Universal Bias), (3) SBIden (Identification of Seasonal Bias), and (4) SBElim (Elimination of Seasonal Bias). Module UBIden was programmed to identify the Universal Bias. Module UBElim is activated if the Universal Bias is identified, for only the electricity profile or gas profile, or both profiles. If there is no Universal Bias, a Seasonal Bias must exist and the Module SBIden will run to identify the specific type of Seasonal Bias. This is followed by the use of the SBElim module when the Seasonal Bias is identified. These four modules are then used to sort out a parameter which will be tuned for the iteration step. Fig. 4 shows a flow chart of this automated calibration algorithm.

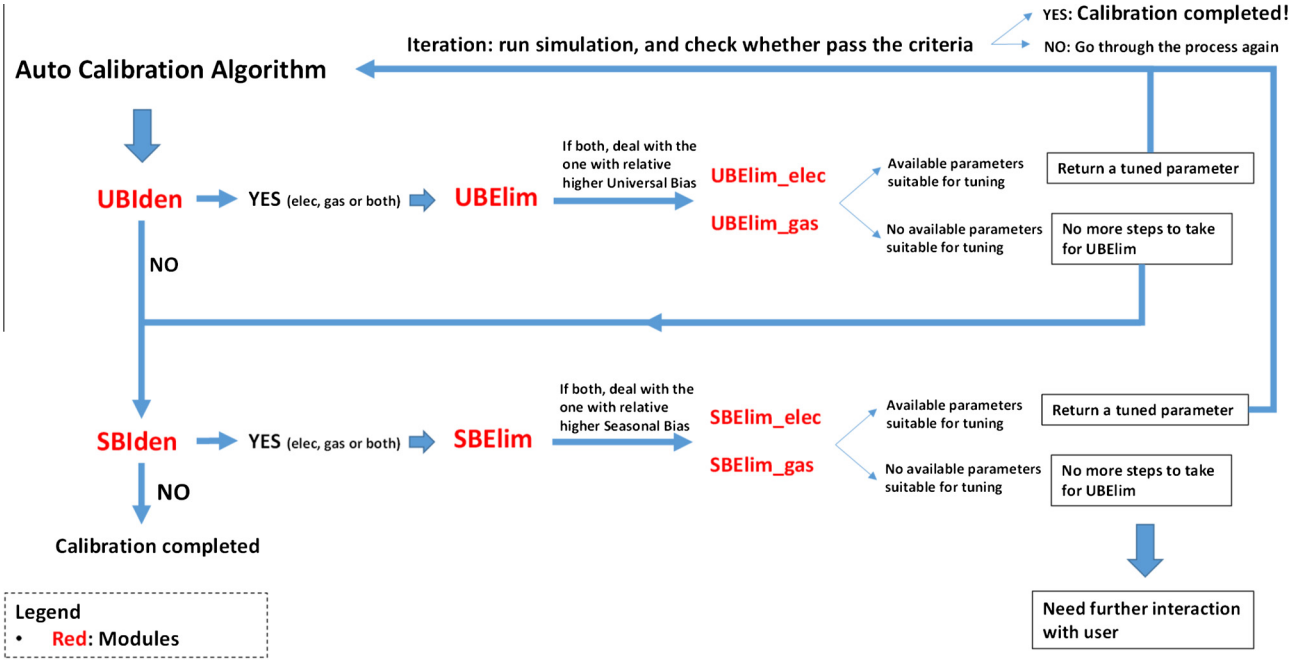

Fig. 4. A flow chart of the automated calibration algorithm.

2.5.1. Modules to identify and eliminate the Universal Bias

Module UBIden identifies the Universal Bias, by recognizing that the simulated data is consistently higher or lower than measured data in 11 or more months. Module UBElim becomes activated only if the Universal Bias is identified. There are two sub-modules: UBElim_elec and UBElim_gas, which are used to manage the iteration process with the goal to eliminate the Universal Bias that exists between the simulated and actual electricity and gas profiles, respectively. If a Universal Bias in both electricity and gas profiles exist, an index of the relative Universal Bias for each energy type is compared. The indices are calculated using the following order: (i) the biases for each month are ranked and (ii) the minimum of the remaining biases are averaged. The index is calculated by dividing the average value by the total energy consumption for the respective energy type (electricity or natural gas). This represents a weighted average of the Universal Bias to the total energy consumption for the energy type in question. Likewise, if the Universal Bias is negative, the index is calculated in the same fashion, except that the numerator is the average of the maximum bias.

2.5.2. Modules to identify and eliminate the Seasonal Bias

SBIden is activated under the precondition that there is no Universal Bias or that no more action can be taken for the Universal Bias to be eliminated. Similar to UBElim, the SBElim module is activated when a Seasonal Bias is identified, either in electricity, gas, or both profiles. There are two sub modules: SBElim_elec and SBElim_gas, are used to adjust the simulated electricity and gas profiles, respectively. If the Seasonal Bias exists for both load shapes (electricity and gas), an index indicating a comprehensive Seasonal Bias will be calculated as the sum of absolute NMBE and CVRMSE of the energy type. The energy type with the higher index will be attended to first.

3. Implementing the automatic calibration and a case study

The automatic model calibration technique was developed using Ruby, an object-oriented, general-purpose programming language and built on top of OpenStudio. The application was made accessible to users through the development of a web-based platform called the Commercial Building Energy Saver or CBES toolkit [51]. The CBES toolkit is intended to be used for small and medium office and retail buildings in California. It provides energy benchmarking and three levels of retrofit analysis considering the project goal, data availability, and user experience. CBES offers prototype building models for seven building types, six vintages, in 16 California climate zones and roughly 75 energy conservation measures (ECMs) for lighting, envelope, equipment, HVAC, and service hot water retrofit upgrades [52]. The CBES Detailed Retrofit Analysis, the most advanced level of the three levels of retrofit analysis, utilizes the automated calibration algorithm. The calibration attunes inputs prior to on-demand energy simulations using OpenStudio and EnergyPlus to calculate the energy performance of the building with user configurable ECMs. The goal of the calibration is to be able to get a more accurate estimation of the energy savings of the retrofit measures for the building, by capitalizing on having a simulated building profile that closely resembles the actual building. Fig. 5 shows the interface of the CBES toolkit, with the 'Building Model Calibration' tab highlighted. The interface allows for automatic or customized calibration using the pattern-based methodology developed in this paper.

The tuning range and selection can be fully automated or a customized calibration feature can be used. The customized calibration allows the user to select which parameter they would like to change and enter a tuning range. The customized calibration feature enables users who have confidence in their inputs, to choose to exclude specific parameters from the list of possible changeable parameters during the calibration process. Alternatively, if users know the possible range (maximum and minimum value) for the input parameters this can be included to aid in the calibration process. The more information the user provides the faster the calibration process will find a solution. Fig. 6 shows a screen shot of the customized calibration web-app. The image shows options allowing the user to select which parameters to tune or to let the computer algorithm decide on a suitable parameter range. For those parameters that the user overrides, a minimum or maximum range has to be specified.

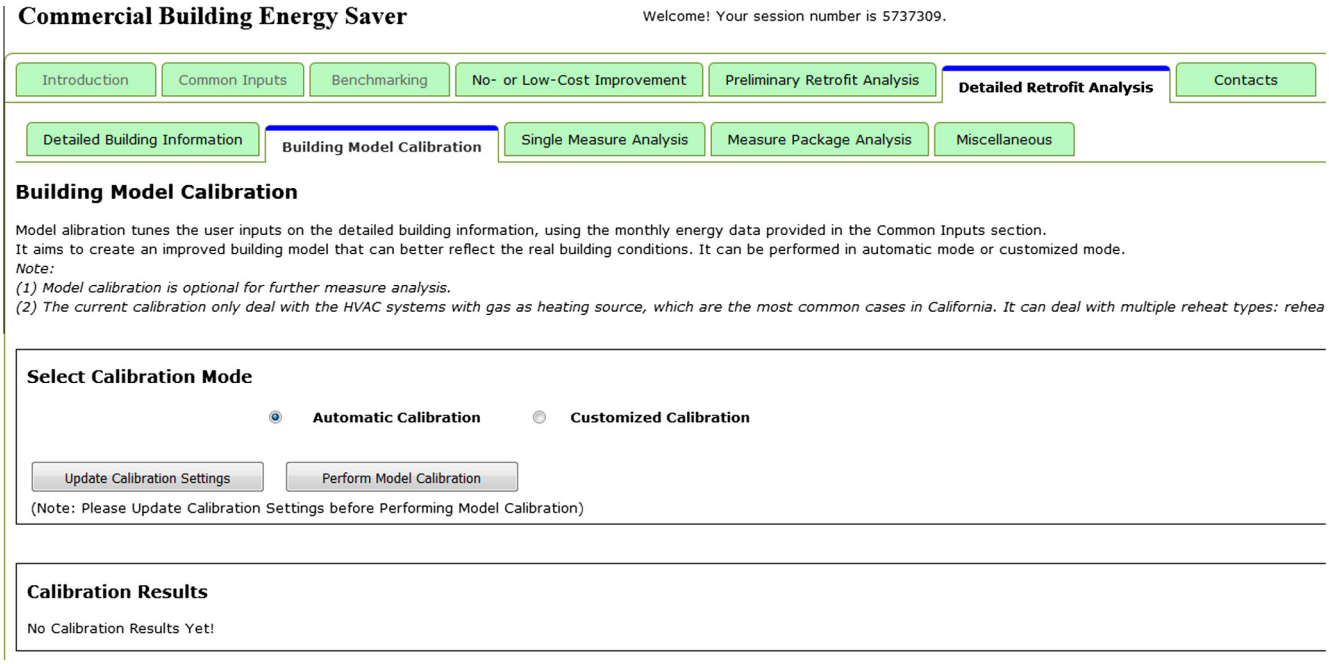

Fig. 5. The interface of the CBES toolkit showing the building model calibration feature.

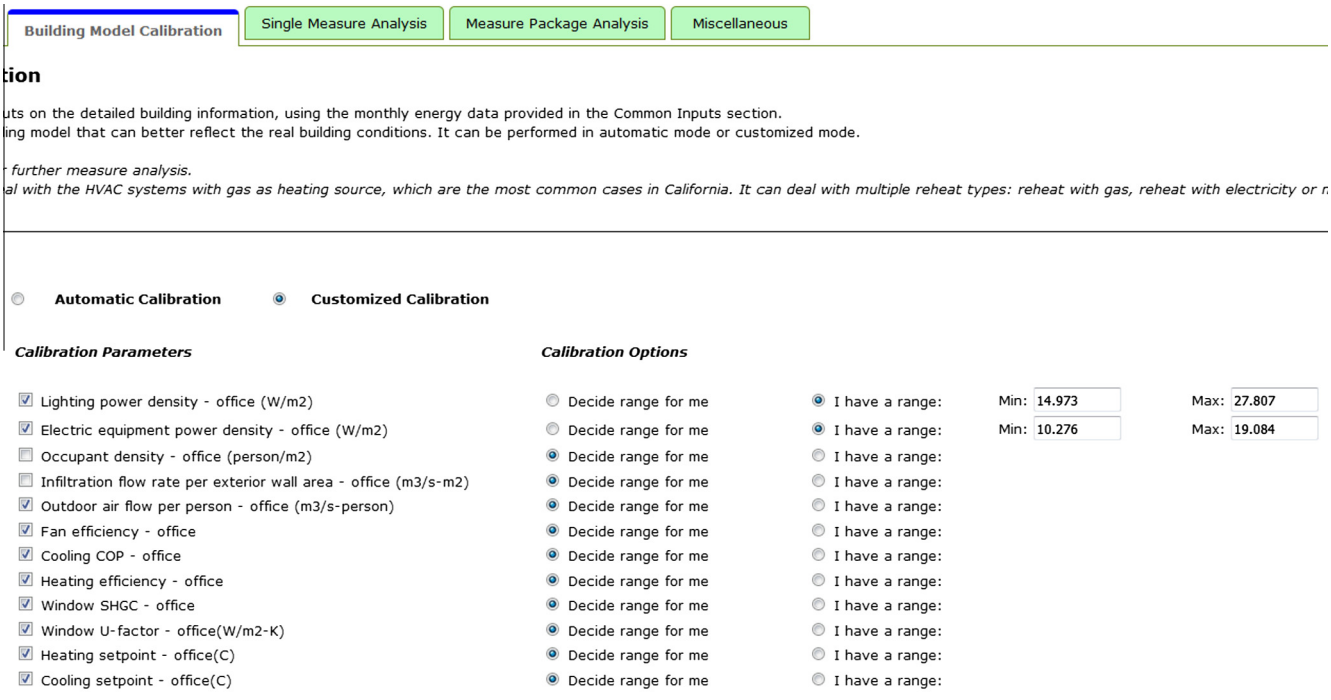

Fig. 6. Interface of customized calibration using the CBES toolkit.

To demonstrate the application of automatic model calibration, a single story, small (929 m^2 or 10,000 ft^2) office building located in San Francisco, California (zip code: 94127) and built in 1977, was used. The basic information of the building, including building type, vintage, location, and building area was entered in the CBES Web APP into the common inputs tab. For simplicity, additional details about the building, such as: (i) lighting power density, (ii) insulation, (iii) window specifics (*U*-value, solar heat gain coefficient, visual transmittance), (iv) internal loads, (v) HVAC system, (vi) occupancy, lighting, HVAC and setpoint schedules, (vii) water heater information and (viii) utility rates were taken from the CBES default settings. The default settings were generated from California's building energy efficiency standards Title 24 [53] and ASHRAE Standard 90.1 [48]. San Francisco belongs to California Climate

Zone 3 [48] classifying the climate as *Mild* according to the CDD and HDD calculation. The HVAC system of the building was a packaged single zone rooftop unit with no reheat.

3.1. Calibrating the case study

Before the start of the calibration process the monthly energy consumption of the original model was simulated. Module "UBIden" was called to check if there was a Universal Bias pattern. In this particular case, a positive Universal Bias for the electricity profile and a negative Universal Bias for the gas profile were identified (Fig. 7(a_E, a_G)). This result triggered the "UBElim" module. Due to the fact that a Universal Bias was identified for both electricity and gas profiles, the index of the relative Universal Bias was calculated. The index showed that the electricity profile had a larger Universal Bias, triggering the module "UBElim_elec" and start of the tuning process.

Tuning Step 1: The goal of tuning step 1 was to eliminate the Universal Bias in both the electricity and gas use profiles. Using the calibration algorithm, in combination of a *Mild* climate and no reheat, resulted in changing the lighting power density as the first parameter to tune. In this step the lighting power density was reduced from 21.4 to 15.0 W/m^2 (Fig. 7(b_E, b_G)).

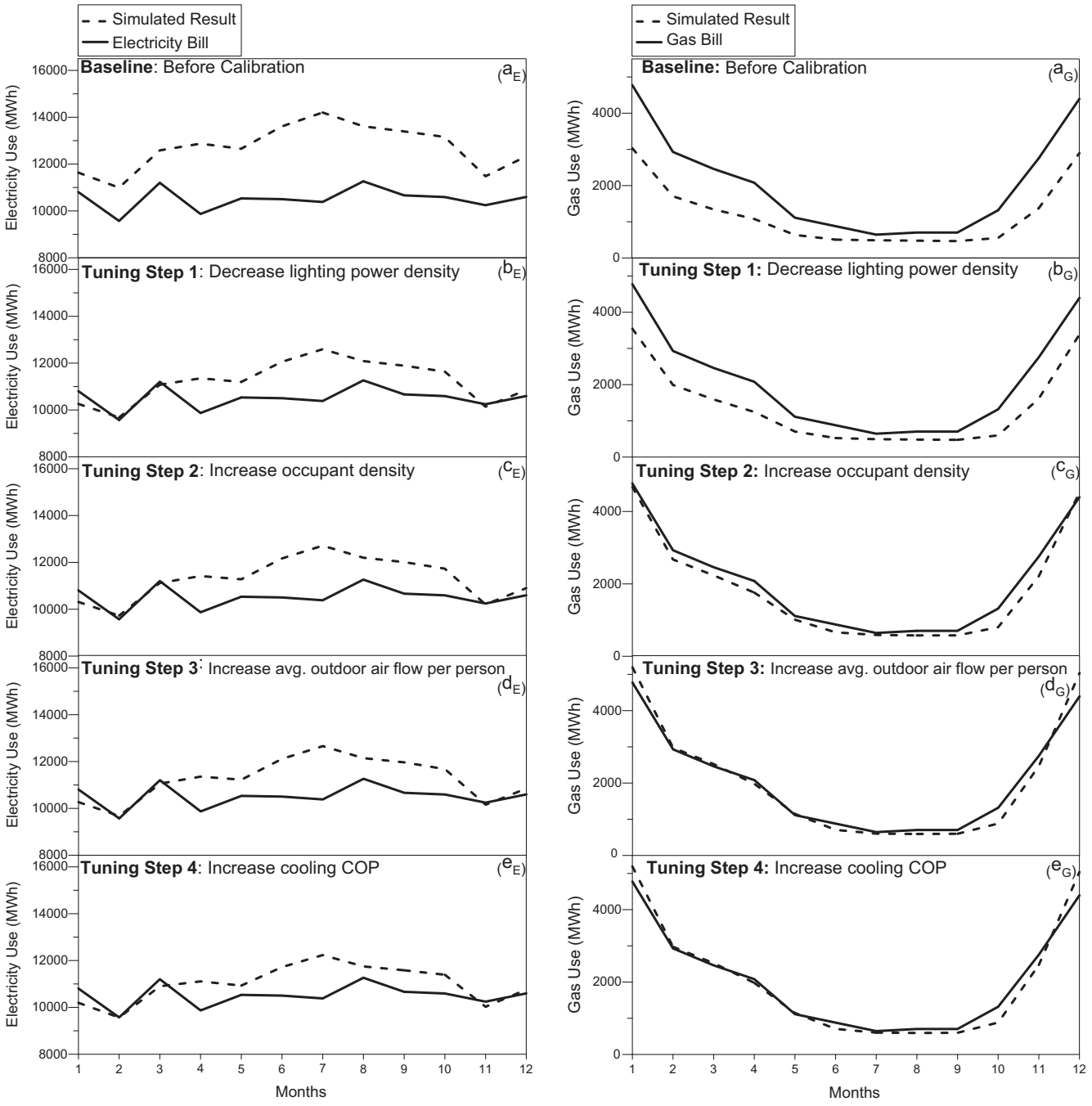

Fig. 7. The simulated results compared with the actual electricity (E) and gas (G) usage: (a_E) and (a_G) the baseline prior to calibration; (b_E) and (b_G) tuning step 1: the results following a decrease in the lighting power density; (c_E) and (c_G) tuning step 2: the results following an increase in occupant density; (d_E) and (d_G) tuning step 3: the results following an increase in the outdoor air flow per person; (e_E) and (e_G) tuning step 4: the results following an increase in the cooling COP.

Tuning Step 2: The resulting profile from tuning step 1, showed a negative Universal Bias for the gas profile and a Seasonal Bias for the electricity profile. With a Universal Bias still identified, UBElim_gas continued the process. The next parameter to be tuned was the occupant density, with an increase from 0.11 to 0.14 persons/m^2 (Fig. 7(c_E, c_G)). Due to the fact that the goal of the parameter selected in this step was to eliminate a Universal Bias in the gas profile, the parameter may not improve the electricity profile. In fact this became the case, where Fig. 7 (c_E) showed little to no improvement relative to Fig. 7(b_E).

Tuning Step 3: After tuning steps 1 and 2, all Universal Bias patterns were eliminated, at which point the SBIden module was triggered. A positive Seasonal Bias for electricity and a negative Seasonal Bias for gas were identified, triggering module SBElim. The indices of relative Seasonal Biases for the two energy types were calculated as 18.9 for electricity and 22.1 for gas. The indices show that the gas profile had a relative higher comprehensive Seasonal Bias triggering the SBElim_gas module. Again the selection of the parameter aimed as adjusting the gas profile. Based on the priority list for this specific bias combination, the outdoor air flow per person was selected as the third parameter to be tuned. This was increased from 0.00708 to 0.00769 m^3/(s person) (Fig. 7(d_E, d_G)). As in tuning step 2, the parameter did not improve the electricity profile, where Fig. 7 (d_E) showed little to no improvement relative to Fig. 7(c_E).

Tuning Step 4: Lastly, a positive Seasonal Bias for electricity and a positive Seasonal Bias for gas were identified. The indices of their relative Seasonal Biases were 18.0 and 15.3, respectively, triggering the SBElim_elec to be used. Using a similar method to tuning step 3, the cooling COP was selected as the fourth parameter to be tuned. The original COP input was 3.1, which was adjusted to 3.7 (Fig. 7(e_E, e_G)). In this case, optimization of the electricity profile was targeted. Adjusting the cooling COP will not affect the gas profile as indicated that Fig. 7(d_G) and (e_G) are the same.

Following tuning step 4 the NMBE was less than 5% and the CVRMSE was less than 15% for both profiles, ending the calibration process. Table 3 shows the parameter values before tuning and when tuning was completed in addition to the resulting NMBE and CVRMSE for the electricity and gas profiles following each tuning step. The entire process was performed using an eight-core desktop and took about 8 min to complete. It should be stressed that the parameter selected may or may not improve one of the two profiles, depending upon which module is operating during the iteration step. This can be clearly seen in the NMBE values for electricity in steps 2 and 3, where the parameter selected is intended to impact the NMBE of the gas profile (Table 3). Similarly, it can be shown that the CVRMSE values in steps 3 and 4 for the gas profile are the same, where the parameter selected (cooling COP) only impacts the electricity profile (Table 3). This is intentional, such that the pattern index which indicates the worst profile performer will dominate the parameter to be selected for adjustment.

4. Discussion

4.1. Novelty of the automatic calibration process

Using only the inputs of the monthly electricity bill and gas bill, the raw building energy model and weather data, a calibrated model could be achieved following an automatic iterative process. The main findings showed that it is possible to integrate the intelligence and experience of the modelers into an automated calibration process, by linking the tuning of the parameters based on the generic patterns. This logic was able to be programmed considering the bias pattern, understanding the possible causes of specific patterns under different conditions and which parameter should be tuned first. These were summarized into principles, according to which the patterns were identified and the parameters were selected and tuned accordingly. In this way, calibration could be automated as well as logical. There are basically two types of generic bias patterns, Universal Bias and Seasonal Bias. Universal Bias had the characteristic that the monthly electricity bill is always higher (or always lower) than simulated results, while for Seasonal Bias, the bias during cooling-dominant months was significantly bigger/smaller than the bias during heating-dominant months, or even had an opposite sign. To further address the influence of the climate on the bias patterns, 5 climate types are defined in this research: *hot all year round*, *cold all year round*, *hot summer & cool winter*, *warm summer & cold winter* and *mild*. The algorithm of automated calibration was developed with four modules: UBIden, UBElim, SBIden and SBElim. The Universal Bias, which was more simple and straightforward, was always the first to be addressed, followed by Seasonal Bias. On the basis of the CBES web-based platform an application of automatic model calibration was used to demonstrate the developed methodology. The findings from the case study helped to identify and understand the different characteristics of bias patterns between simulated monthly energy consumption and utility bills. More broadly the case study demonstrated the success of the applied logic in the pattern-based calibration methodology.

4.2. The adjustment of schedules

Previous studies show that schedules are very important parameters in model calibration. They have significant impacts on the energy consumption and are difficult to adjust [9,19,23,33]. In the pattern-based calibration method, the HVAC operation schedule, cooling setpoint schedule, heating setpoint schedule, lighting schedule and electric equipment schedule are adjustable parameters in the algorithm (Table 1). The HVAC operation schedule, cooling setpoint schedule and heating setpoint schedule are directly related to the energy consumption of HVAC systems. As mentioned in Sections 2.1 and 2.3, the cooling-related/heating-related parameters, including these HVAC schedules, may lead to Universal Bias in cooling-dominant/heating-dominant climate types (Hot all year round/Cold all year round); while they may cause Seasonal Bias in climate types with distinct cooling

Table 3
Tuning steps and the calibration index after each tuning step.

Tuning	Calibration actions	Before tuning	After tuning	NMBE Electricity (%)	NMBE Gas (%)	CVRMSE Electricity (%)	CVRMSE Gas (%)
	Baseline prior to calibration			20.8	−41.2	23.4	50.7
Step 1	Decrease lighting power density (W/m^2)	21.4	14.9	6.8	−32.7	10.6	38.9
Step 2	Increase occupant density (person/m^2)	0.11	0.14	7.6	−9.9	11.3	13.8
Step 3	Increase average outdoor air flow per person (m^3/s person)	0.007	0.008	7.1	−0.2	10.9	14.1
Step 4	Increase cooling COP	3.1	3.7	4.7	−0.2	8.5	14.1

and heating seasons (hot summer & cool winter, warm summer & cold winter). Therefore, these HVAC schedules will have higher priority in the calibration process when there is a Universal Bias in the hot or cold year-round climates, or there is a Seasonal Bias in other climates with distinct cooling and heating seasons. The lighting schedule and electric equipment schedule serve as the supplementary parameters for lighting power density and electric equipment power density. When lighting power density and electric equipment power density have been adjusted to their upper or lower limits, these two schedules will then be tuned.

When adjusting the HVAC schedule, with a value of either 0 (off) or 1 (on) at each time step, operation hours on weekdays and weekends are increased or reduced; The lighting schedule and electric equipment schedule, varying between 0 (fully off) and 1 (fully on), are adjusted by scaling up or down all the schedule values; The cooling and heating setpoint schedules are adjusted by increasing or decreasing all the setpoint values by a delta temperature.

4.3. Pros and cons of the automatic calibration process

The pattern-based calibration method has both pros and cons relative to traditional methods. Manfren et al. [54] highlighted the general problems with model calibration including (i) intensive computational resources, (ii) exploration of the parameter range can be infeasible, (iii) various ranges or combinations of input variables may yield similar results, (iv) observed data contains error and uncertainty and (v) model response is multivariate. The automatic calibration process overcomes some of these generic problems, but not all. Firstly, the automatic calibration process still relies on a pre-defined intelligence that determines the set of model parameters to tune from different patterns. Although this method is a vast improvement over conventional calibrations, which typically rely on a generic hierarchy, there can still be improvement in making the approach more physics-based. The use of bounded parameter ranges following the ASHRAE Guideline 14 [49] criteria can't assess whether the range is feasible, leading to potential calibration errors. Items which can be improved upon include: (1) a larger availability of building types as currently the calibration model only applies to small to medium buildings; (2) the number of changeable parameters are limited, so the algorithm is not able to find a reasonable solution when parameters (other than the current 17 parameters) are far away from the true values. More parameters with relatively higher sensitivity to energy consumption are to be investigated and added to the algorithm as changeable parameters; (3) the heating source that is available for automated calibration is limited to gas only for now. Electricity heating will be added to the algorithm in the future; (4) the use of monthly data and not hourly or smart meter data is a simplification that sacrifices accuracy for computational simplicity; (5) the "priority lists" for selecting the to-be-tuned parameters on a certain bias pattern in different climate and reheat types are concluded from the local sensitivity analysis results of a DOE reference medium office building. Though local sensitivity analysis has low computational costs, and is simple to implement and easy to interpret, it does not consider interactions between inputs and does not have self-verification [55]. This current "priority list" is not generic enough to ensure success of calibration for other building types. To get a more comprehensive and robust overview of the parameters' influence on the energy consumption, a database of the parameters' sensitivity under different circumstances is preferred. Since there are a number of building types, climate types, reheat types and changeable parameters, the combinations of the cases could be hundreds of thousands. Considering the large amount of computation, a supercomputer might be utilized to generate the database. It should be noted that even if a supercomputer is used to generate the database, this would be a preprocessed one-time job. The generated database could serve as a look-up table when selecting to-be-tuned parameters, which means that the supercomputer is not needed during the automated calibration.

Lastly, despite our best efforts, the algorithm is not fail proof. If the simulation fails to converge, the iterative calibration process automatically stops, with the results indicating a partially calibrated model. Based on our tests of more than a hundred cases which cover all the climate types and reheat types in the study, about 80% of the tested cases converged using this calibration process.

Despite these limitations, the automated model calibration process is a logical calibration process, with a well-documented methodology to support the automatic tuning of parameters generated from comparing simulated and measured data. In addition the process is quick to run on a PC improving upon the intensive computational resources required during most calibration processes. The automated feature affords advantages such as the potential to be scaled-up and the ability to offer a calibration process at a relatively low cost.

5. Conclusion

This paper presented a new approach to achieve automated calibration of building energy models using graphical pattern identification, instead of traditional automated calibration through mathematical optimization techniques. The key findings and basic methodology are: (1) parameter selection and tuning could be intelligent and automated following logic that summarized principles of different pattern biases; (2) two types of bias patterns, Universal Bias and Seasonal Bias were identified according to their characteristics; (3) the algorithm of automated calibration was developed and implemented in the CBES web-based platform. The demonstration of the automatic model calibration for a small office building showed the capabilities of the methodology. The pattern-based automated approach is able to integrate logic linking parameter tuning with the bias pattern identification, removing any need for manual input or long computation time. Future work will focus on enhancing the algorithm for: (1) more robustness and better computing performance, (2) a wider range of building types, (3) more tunable model parameters, (4) more heating source options, and (5) calibration to hourly load shapes and peak demand.

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