An automated optimization method for calibrating building energy simulation models with measured data: Orientation and a case study

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HIGHLIGHTS

- A complete and inclusive optimization automated calibration flow is developed.
- Sensitivity analysis is applied to determine the target tuned parameters.
- PSO is adopted and compiled to perform the optimization procedure.
- Sub-metered energy use are simultaneously calibrated through a weighted function.
- A case study in Shanghai based on sub-metered energy data is presented.

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ABSTRACT

Due to the discrepancy between simulated energy consumption and measured data, it is essential to calibrate building energy models to improve its fidelity in evaluating the performance of retrofitting. Currently, most calibration methods are conducted manually to minimize this discrepancy, heavily relying on the knowledge and experience of analysts to discover a reasonable set of parameters. Because of the myriad independent and interdependent variables involved, the reliability of the entire simulation is largely undermined. In the presented paper, we propose a complete and fluent optimization automated calibration flow by introducing the mathematical optimization method (Particle Swarm Optimization is adopted) into the building energy model calibration process, thus leveraging the advantages of the efficiency and flexibility of the automated computer procedure. This approach is also characterized by its inclusivity, for it is compatible with other advanced manual methods and able to largely assist the experts in improving the efficiency of tuning relative input parameters. Moreover, a case in Shanghai is presented to verify the validity of the proposed method. After calibration, the simulation model demonstrates a satisfactory predicting accuracy. The calculated electricity consumption from the HVAC, lighting and equipment matches the actual monitored data with 11.6%, 7.3% and 7.2% CV (RMSE), respectively, and the total electricity consumption is within 6.1%.

1. Introduction

1.1. Original significance

Energy problems have become increasingly hot topics in the world, and the relationship between the demand and supply of energy use has also been of great concern. Buildings contribute significantly to the total energy use on the global scale and are responsible for 40% of energy consumption and one-third of Greenhouse Gas (GHG) emissions [1–4]. Therefore, buildings are important in the overall strategy of energy conservation and emissions reduction; energy goals will be achievable if we focus more on the retrofitting of buildings. At the same time, various reports and researches indicate that some adverse factors, such as defective building design without sufficient consideration of energy conservation, the degeneration and faults of the HVAC system, and changes in manipulation strategies, all result in the unsatisfactory energy efficiency of building operation. To ensure the practical

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contribution of buildings, it is critical to introduce several retrofit programs in existing buildings immediately. Mills et al. [5,6] believed the United States will achieve 16% median energy savings if the operation of existing buildings is improved. If these retrofit methods associated with building envelopes, mechanical equipment, and lighting systems are applied in commercial buildings in the USA, the reduction in money conversed from the potential energy savings will reach 30 billion in approximately 2030. In China, building energy efficient retrofitting is also significant. In the north of China, the floor area of inefficient existing residential buildings is 4.16 billion m^2, accounting for 76.33% of the total northern residential building [7]. To address this issue, the Chinese government released the "Green Building Action Plan" [8], aiming at retrofitting 570 million m^2 of existing buildings by 2015. Meanwhile, subsidies of approximately \$7.0/m^2–\$8.6/m^2 are provided to facilitate implementation of this plan [9].

1.2. Building energy model calibration

Before initiating the building retrofit program, it is necessary to evaluate the cost-efficiency of various proposed energy saving measures. The main approaches usually applied to evaluate the building energy consumption are measurement and simulation [10]. Due to its convenience and efficiency, the latter, building energy simulation (BES), is always recommended by the researchers [11–13]. However, although this technique has been developed mature gradually for many years, one problem still exists. That is the discrepancy between the calculated results in the energy simulation and the monitored data in actual buildings [14]. This deviation mostly results from the differences between the initial design and practical operation [15], such as using default/standard values for parameters [16], which are difficult to be described in the building energy model. In most situations, it is essential to calibrate the model to at least roughly match the given actual building, thus increasing its fidelity in the energy evaluation. Only if the energy model is properly calibrated, could it be applied reliably to implement such studies as evaluating the potential energy saving from various energy conservation measures (ECMs), or predicting the future energy consumption.

The building energy model calibration involves tuning miscellaneous input parameters to minimize the aforesaid discrepancy. This process is usually conducted based on various available monitored data of energy behavior [17,18]. If the virtual monitoring system is well-established in the target building and can record hourly energy consumption, open-closed state data on time scales [19–21] and the operational data in different zones or systems on spatial scales [22], it will greatly facilitate the analysts and increase the efficiency and accuracy of the calibrated model. Coakley et al. [23] summarized the hierarchy of some source information in his research, as presented in Fig. 1. Apparently, the smaller time and spatial scale the monitored data are divided into, the more accurate and difficult it is to achieve the synthetic calibration [19]. However, at present most buildings are not equipped with the monitoring system, and the monthly end-use of energy consumption comes available in a better situation.

So the question comes: What constitutes a qualified building energy model? Its accuracy is currently confirmed by the fact that outputs generated by the model should closely match the measured utility data, which also conversely relies on how accurate the inputs could represent the properties of the given actual building [22]. To address the errors between the model simulation results and the measured data, Error (ERR) (calculated by Eqs. (1) and (2)) and Coefficient of Variation of Root Mean Square Error (CV(RMSE)) (calculated by Eqs. (3)–(5)) are specified by three relative guidelines: American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Guideline 14 [24],
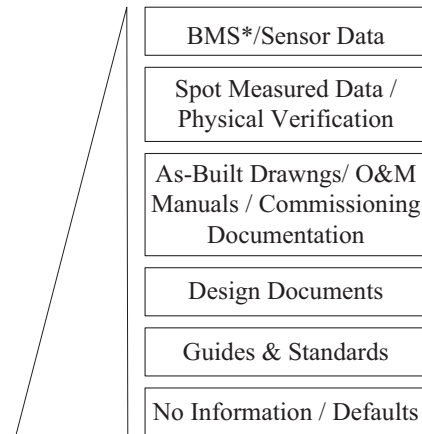

Fig. 1. The hierarchy of various source information [23] (*BMS: Building Management System).

International Performance Measurement and Verification Protocol (IPMVP) [25], and Measurement and Verification of Federal Energy Projects (FEMP) [26], as presented in Table 1. Some researchers [17,27] validate and recommend *Mean Bias Error* (*MBE*) and *CV (RMSE)* for the tolerance evaluation of model calibration.

Apart from the authoritative criteria for error evaluation, there is no uniform calibration method [28–30]. Nevertheless, for the procedure of calibrating model, some experts have made their own clear descriptions [24,28,31–34], of which the most detailed and prevailing is from ASHRAE-14: (1) Make a calibrated simulation plan, (2) Collect data, (3) Input data and run the model, (4) Calibrate the simulation model, (5) Tune the error, (6) Calculate the energy, (7) Build a baseline model and post-retrofit model, (8) Summarize and report.

$$ERR_{month} \ (\%) = \left[\frac{(M-S)_{month}}{M_{month}} \right] \times 100\% \tag{1}$$

$$ERR_{year} \ (\%) = \sum_{month} \left[\frac{ERR_{month}}{N_{month}} \right] \tag{2}$$

$$RMSE_{month} = \left[\frac{\sum_{month}(M-S)^2_{month}}{N_{month}} \right]^{1/2} \tag{3}$$

$$CV(RMSE_{month})(\%) = \left[\frac{RSME_{month}}{A_{month}} \right] \times 100\% \tag{4}$$

$$A_{month} = \frac{\sum_{month} M_{month}}{N_{month}} \tag{5}$$

where *M* is the measured electricity (kW h), *S* is the simulated electricity (kW h), N_{month} is the number of annual utility bills, and A_{month} is the averaged measured electricity (kW h).

The specific calibration method of establishing the energy model, namely how the process of adjusting the inputs in the models is conducted, is absolutely the focus of the current research. Experts and scholars have explored some significant achievements

Table 1
Acceptable range of monthly data calibration [24–26].

Index	ASHRAE 14	IPMVP	FEMP
ERR_{month}	±5%	±20%	±15%
ERR_{years}	–	–	±10%
$CV(RMSE_{month})$	15%	5%	10%

in the formal and systematic calibration methodologies. According to the reviews from Reddy [28], Coakley [30] and Fabrizio [29], a large number of researchers concentrate on manual calibration, with different nuances. This approach largely relies on the modelers' professional experience and judgment, which guide them to empirically perform iterative tuning of the model input parameters. Manual calibration does not mean continuous fudging or trial-and-error process solely conducted through the human's brain, more like an art. It also requires reasonable logic, methods and tools. A typical method is to obtain measured data through additional approaches, such as energy consumption bills [27], on-site visits [35], interviews with operators [17], short-term energy monitoring (STEM) [36–38], and operational or environmental data collection [39]. These data are used as supplemental evidence to improve the calibration. Yoon et al. [17] collected the basic data needed for simulation (including building data, utility data, and weather data) and developed an initial corresponding energy model. At this step, the CV(RMSE) of electricity reached 24.9%, exceeding all recommended criterion. After that, they analyzed the base load consumption (weather independent electricity or gas usage) and calibrated the model in swing-season, referring to the data from monthly energy consumption and STEM. Then, they conducted additional on-site visits and interview, confirming the internal loads - the lighting, equipment, and people, through which they continued to complete the calibration for the building energy model in the heating/cooling season. The emphasis of this step is on the HVAC system. Eventually, the CV(RMSE) of electricity dropped to 3.6%. Later, this type of calibration method gradually gained comprehensive acceptance and various extensions [17,20,27,39,40]. In addition to this method, there are some researchers developing alternative approaches applicable in different scenarios. To display the differences between simulated and measured results intuitively, Kandil et al. [41] introduced the calibration signature in the building energy model calibration. This signature is defined as the normalized plot as a graphical representation. Including calibration signature [17,42], the graphical techniques have been repeatedly applied in building energy model calibration [21,43–45]. To guarantee the simultaneous accuracy for multiple levels of simulation, Yang et al. [22] developed a simultaneously multi-level calibrating framework, including building-level, ECM level and zone-level. They also constructed the classification of building parameters to more clearly understand and evaluate the parameters to be monitored and adjusted. Using the previous experience and knowledge as references, Raftery et al. [20] proposed an evidence-based approach, which trace the previous detailed versions of calibration to help make adjustments to model parameters. This methodology requires additional visible inspection for verification. For the situation that the different types of electricity data are mingled in the energy bills, Ji et al. [19] introduced the Fourier series model to disaggregate the hourly non-HVAC electricity consumption from power meters and finally developed a bottom-up calibration method based on the hourly energy consumption data.

The advantages of manual calibration are the full use of the knowledge of professionals, and some researchers even consider to compile these experiences into the knowledge base [20] to achieve greater promotion and applicability. However, the drawback also exists. Because the manual calibration wholly relies on hard-operated skill, adjusting the parameters involved in this process tends to consume a large amount of time, which results in the risk of possible inaccuracy. In addition, because of the changeable operation of buildings, the process is even more time-consuming when conducting periodic synchronous calibration. Consequently, to increase the working efficiency, it is natural to think about taking advantage of the computers to implement the manual process with the aid of automated means. This strategy is developed as

automated calibration, which is defined as the approaches without consideration of user driven [30].

The main commonness of automated calibration is to search out a good fitting set of inputs through computational program. Considering the evidence that the process of manually tuning the parameters to match the simulated model and actual building can be recognized as an optimization problem, researchers started to address the ability of numerical optimization. Actually, mathematical optimization method, usually combining numerical simulation and a mathematical method, has been widely and successfully used in the other fields of the building life circle, such as sustainable design and operational control [46,47]. This process is generally integrated in specialized optimization software called Genopt, which is an open platform developed to help determine optimal solutions [48]. To perform the optimization in the calibration process, some forms of objective functions are established to visualize the difference between the simulated and the measured data and is then considered as the basis to calibrate the target model. During the optimization process, the objective equation is different with the variation among direct use of ERR, MBE, RMSE, and CV(RMSE) between simulated and measured data [30,49,50]. Some other analysts tend to apply the weighted function, combining the CV(RMSE) and Coefficient of determination R^2 to minimize the error and ensure the goodness of fit simultaneously. The target basis for optimization also varies, some with indoor temperature [51–54] and some others with energy consumption [49,50]. For the detailed optimization-based automated approaches, Sun et al. [55] proposed a universally feasible statistics-based calibration framework for building energy simulation: sensitivity analysis (evaluating the influence of variables on building energy), recognition analysis (filtering out the subset of parameters to be tuned), mathematical optimization (calibrating the initial model), and uncertainty analysis (determining the possible range of variables). Later, Tahmasebi et al. [52–54] and Taheri et al. [51] proposed further improved method and process for determining the variables to be tuned. With the aid of their own knowledge and experience, they selected an initial set of 23 parameters, including a range for each one. Then, Monte Carlo sensitivity analysis was applied to screen out the subset of 4 influential parameters to be adjusted. Coakley et al. [56] performed a Latin-Hypercube Monte Carlo (LHMC) analysis to develop the bounded grid search, and then simulated each set of variables to be tuned and calculated the statistical goodness-of-fit one-by-one specifically. These solutions were eventually ranked and filtered into the top 100 as the final 'set of calibrated solutions'. Meanwhile, after determining the range of each variable, Monetti et al. [49] performed the mathematical optimization process using the software GenOpt. In order to reduce the time consumed in the process of numerical optimization, Zheng et al. [57] applied the meta-model technique, which integrated sensitivity analysis in the calibration. They developed a database of calculating samples with the parameters varying around the nominal values. Based on that, the sensitivity analysis and optimization is conducted in 2 h and 2–3 s respectively. But there is a premise underlying this approach, namely the best-fitting set of inputs exists in the pre-developed database. Another major deficiency of this approach is that it is more exclusive and wholly neglect the knowledge of experts.

The application of numerical optimization in the calibration process facilitates engineers' and researchers' works greatly, but sometimes this type of automated calibration method tends to abstract the physical objective to a pure mathematical problem, neglecting some physical meanings of actual buildings. Indiscreet overuse could result in accurate matching mathematically, but inaccurate matching physically. This is just the reason why some researchers criticize the automate calibration, and why it is developed slowly. Therefore, it should be noted that the automatic

optimization method of model calibration does not act as the role of replacing manual calibration that includes the professional knowledge and experience of researchers and experts. This is one of the reasons for introducing this paper, where the orientation of the numerical optimization method in calibration process is exhibited explicitly. The numerical optimization automated calibration presented in this paper is more likely to act as a supplemental method to optimize the existing manual calibration by transforming the manual adjustment to the automated process, thus greatly improving the accuracy and efficiency of the calibration. Another reason is that with the improvement of the building monitoring system, sub-meter recording of the energy use has emerged in more and more buildings, which further promotes the fidelity of building energy model. In contrast to the previous optimization-based calibration, the new calibration approaches apply the indoor temperature or single energy data as the variables in the cost function. The procedure of these sub-metered data (energy use of lighting, equipment, cooling, and heating) application and the method of simultaneous calibration are also presented.

In this paper, we first systematically expatiate the automated optimization calibration methodology. Since the optimization method has better efficiency if fewer parameters are included in the tuning process [28], we complete the sensitivity analysis [58] in advance. In addition, the result of sensitivity analysis is an important reference for the decision on weighting coefficients of the objective function in the automated optimization calibration. For the detailed method applied in the optimization program, any of optimization algorithms (such as Particle Swarm Optimization (PSO) or genetic algorithms (GA)), of which the goal is to find a set of parameters that meet certain objective results, can be used. We choose PSO in this paper and compile the external optimization program with it. Next, an actual case in Shanghai is presented to verify the validity of the proposed method. Finally, we discuss and explore the scope and limitations of this method.

2. Calibration methodology

The proposed calibration method needs to be resolved to build a robust and reasonable model, as presented in Fig. 2. The main steps in this paper are the sensitivity analysis (finding the most influential parameters) and automated optimization calibration (using particle swarm optimization), which are specified as follows.

2.1. Sensitivity analysis of the input parameters

The selection of the input parameters (including weather, envelope, air conditioning system, and operating schedule) is an essential part of the calibrated simulation. Sensitivity analysis is an effective tool to assess the impact level of input parameters. Additionally, sensitivity analysis is suitable for the preparatory work of building simulation.

2.1.1. Building model

A typical office building in Shanghai is built using eQUEST for sensitivity analysis. The building has 25 floors with a height of 4.20 m and single standard floor space of 1750 m^2. The VAV (variable air volume) system is adopted, and the building uses water-cooled centrifugal chillers for cooling and gas boilers for heating. All system parameters are set according to ASHRAE Standard 90.1-2007 [59] and the Chinese design standard for the energy efficiency of public buildings [60]. The energy consumption in this study indicates electricity use. The sensitivity analysis based on such typical model can obtain the basic characteristics of energy use for most office buildings in Shanghai.

2.1.2. Input parameters and evaluation index

According to Lam [61] and Reddy [62], the annual energy consumption of office buildings is sensitive to the fenestration, internal loads, temperature set points, HVAC plant efficiency. In Shanghai, the VAV system is universally applied in office buildings. To explore the influences of inputs on the building simulation model, based on the results of previous researches, we extend the number of studied objects to 13 by three parts – envelope, interior load, HVAC system (see Table 2). Moreover, these 13 parameters are suitable for the practical maneuverability and the guidance of engineering projects.

The energy source of office buildings in Shanghai is mainly electricity and gas, of which the gas is used for domestic hot water and space heating. Because the data of heating boilers are incomplete in the monitoring system, the gas consumption will not be discussed in this paper. But the relative electricity consumption of the distribution system is still included. In addition, some building physical parameters are taken into the consideration, though it is difficult to change them after the building was built as we know. The reason is that the data from the original design specifications and drawings are usually inaccurate, so it is also necessary to adjust them in the calibration process to improve the fidelity of the building model.

The sensitivity analysis is performed using the Morris method. In each run of calculating the building energy change, only one input parameter is given a new value, while the others remain unchanged. Each variable is changed within a defined range of possible values.

To explicitly identify the impact of different input factors on the energy consumption, we calculate P (defined as the energy consumption variation value per unit area) and Q (defined as the energy consumption variation rate per unit area) in Eqs. (6)–(9) to measure the sensitivity of different energy use, such as the total system (defined as A), air conditioning system (defined as B), lighting system (defined as C), and equipment (defined as D). The evaluation indexes are given as follows.

Total energy consumption variation value per unit area:

$$P_{A_j} = \frac{A_j - A_1}{X_j - X_1} \tag{6}$$

Average total energy consumption variation value per unit area:

$$\overline{P_A} = \frac{1}{n}\sum_{j=1}^{n} P_{A_j} \tag{7}$$

Energy consumption variation rate per unit area:

$$Q_{A_j} = \frac{A_j - A_1}{A_1} / (X_j - X_1) \tag{8}$$

Average energy consumption variation rate per unit area:

$$\overline{Q_A} = \frac{1}{n}\sum_{j=1}^{n} Q_{A_j} \tag{9}$$

where X_j is the single-factor value, A_j is the total energy use corresponding to X_j, and n is the number of varying values of the inputting single-factors. A_1 and X_1 is the basic reference, so A_j-A_1 and X_j-X_1 are the changes of the total energy use and the inputting value respectively. Other definitions, such as the energy consumption of the air conditioning system, lighting system and equipment, are similar as above.

2.1.3. Sensitivity analysis results

The external wall is one of the main parts of the envelope structure, the U-value of which directly affects the heat transfer characteristics of the indoor and outdoor environment. The results of the
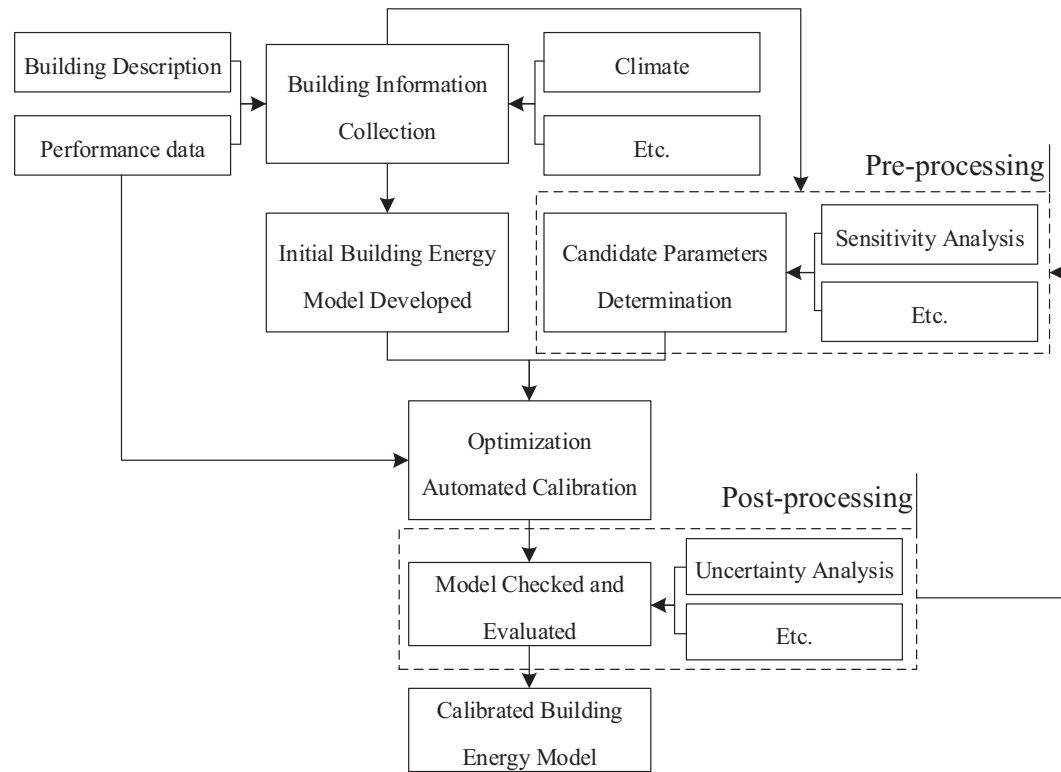
Fig. 2. Schematic diagram of the automated model calibration methodology.

Table 2
Input parameters of the building energy model.

Category	Input parameters			
Envelope	Roof U-value	External wall U-value	Window U-value	Shading coefficient (SC)	Window-wall ratio
Interior loads	Lighting density	Equipment density	Occupant density		
HVAC system	Cooling set point	Fresh air	Chiller COP	Fan efficiency	Pump efficiency

sensitivity analysis are illustrated in Table 3. The average variation of the total annual electricity use per unit area is 0.67 kW h, and the variation rate is 0.64%, which means that when the heat transfer coefficient of the external walls increases 1.00 W/(m² K), the average total annual electricity use per unit area increases by 0.67 kW h. Therefore, the heat transfer coefficient of the external wall has a significant influence on the building electricity consumption.

Table 3
Sensitivity analysis of the external wall U-value.

External wall U-value X/[W/(m² K)]	$j = 1$ 0.50	$j = 2$ 1.00	$j = 3$ 1.50	$j = 4$ 2.00	$j = 5$ 2.50
A/[kW h/(m² yr)]	105.65	105.94	106.31	106.70	107.14
B/[kW h/(m² yr)]	40.76	41.04	41.42	41.81	42.24
P_A/[kW h/(m² yr)]	–	0.58	0.66	0.70	0.74
$\overline{P_A}$/[kW h/(m² yr)]			0.67		
P_B/[kW h/(m² yr)]	–	0.56	0.66	0.70	0.74
$\overline{P_B}$/[kW h/(m² yr)]			0.67		
Q_A/%	–	0.55	0.62	0.66	0.71
$\overline{Q_A}$/%			0.64		
Q_B/%	–	1.37	1.62	1.72	1.82
$\overline{Q_B}$/%			1.63		

Using the same analysis method, we determined the heat transfer coefficient of the other input parameters, respectively, and conducted the modelling calculation. The corresponding results are summarized in Tables 4–6.

From Table 4, we can conclude that the sensitivity of the roof is the smallest among the five factors, whereas the other 4 factors significantly influence the electricity consumption. This is because the typical model is established as a high-rise building, and the area of the roof is relatively smaller compared to the whole building area. Particularly, for the typical office buildings in Shanghai, lighting density is usually fixed, weakly linked with the window-wall ratio, so we do not consider it into sensitivity analysis for typical buildings in this paper.

In Table 5, if the lighting (W/m²), equipment (W/m²) and occupant density (m²/p) increase, the corresponding electricity use will also increase. In addition to influencing the lighting electricity consumption, the lighting density can affect the electricity use of air conditioning system because the lighting devices gradually deliver heat into the indoor air, which could affect the operation of the air conditioning system. A similar situation can also be found for the equipment density. Therefore, internal loads can have a significant impact on electricity consumption.

As shown in Table 6, the electricity consumption of the air conditioning system generally increases with the increase of fresh air and decreases with the increase of the cooling set point, chiller COP, fan efficiency, and pump efficiency. Among the five parame-

Table 4
Sensitivity analysis of other envelopes.

Input	$\overline{Q_A}$/%	$\overline{Q_B}$/%
Roof U-value	0.02	0.05
Windows U-value	0.22	0.58
SC	0.16	0.45
Window-wall ratio	0.14	0.36

Table 5
Sensitivity analysis of internal loads.

Input	$\overline{Q_A}$/%	$\overline{Q_B}$/%	$\overline{Q_C}$/%	$\overline{Q_D}$/%
Lighting power density	3.42	1.51	9.67	–
Equipment power density	3.03	1.49	–	9.96
Occupant density	−2.22	−5.21	–	–

Table 6
Sensitivity analysis of the air conditioning systems.

Input	$\overline{Q_A}$/%	$\overline{Q_B}$/%
Cooling set point	−1.90	−4.74
Fresh air	0.22	0.60
Chiller COP	−5.23	−12.10
Fan efficiency	−0.12	−0.30
Pump efficiency	−0.19	−0.48

ters, the sensitivity of chiller COP is the most significant, and the impacts of the fan efficiency and pump efficiency are the weakest. These results are related to the given air conditioning system.

According to the analysis results in this section, the sensitivity of the envelope is relatively lower compared to the other selected factors, such as the lighting, equipment and occupant density. In addition, the sensitivity of the chiller COP is quite high.

The rank of average sensitivity coefficients of influential inputting parameters is listed in Table 7.

2.2. Optimization calibrated simulation

During modelling, the complexity and accuracy of the calibrations rely on the building information and sub-metered energy use bills, which will determine what input parameters should be tuned and how these works are developed during the calibration. The monitored data are divided into four types of parts, including lighting, equipment, cooling, and heating, of which the former two are applied through rule estimation to be transformed to internal loads to populate the initial model, and the latter two are utilized for other variables' calibration via some type of optimization method, namely, PSO.

2.2.1. Rule estimation

Rule estimation deduced from the theoretical analyses could discover the cause and the solution of the problems.

When the manually calibrated simulation is performed, the discrepancy between the actual and the simulated data implies the necessity to tune the corresponding input parameters. For example, during the course of a specific operation schedule, the lighting

Table 7
List of influential inputting parameters for the typical office in Shanghai.

Items	Subitems	Average sensitivity coefficients			
		$\overline{Q_A}$/%	$\overline{Q_B}$/%	$\overline{Q_C}$/%	$\overline{Q_D}$/%
Envelopes	External wall U-value	0.64	1.63	–	–
	Roof U-value	0.02	0.05	–	–
	Windows U-value	0.22	0.58	–	–
	SC	0.16	0.45	–	–
	Window-wall ratio	0.14	0.36	–	–
Internal loads	Lighting power density	3.42	1.51	9.67	0.00
	Equipment power density	3.03	1.49	0.00	9.96
	Occupant density	−2.22	−5.21	0.00	0.00
HVAC systems	Cooling set point	−1.90	−4.74	–	–
	Fresh air	0.22	0.60	–	–
	Chiller COP	−5.23	−12.10	–	–
	Fan efficiency	−0.12	−0.30	–	–
	Pump efficiency	−0.19	−0.48	–	–

electricity consumption is only related with the lighting density in the model. Therefore, a simple approach to reduce the error is to compare the actual and simulated lighting electricity consumption and then to tune the lighting density. A similar procedure can also be observed in the calibration work of the equipment electricity consumption. Thus, the rule estimation will improve the calibration efficiency by adding simple rules to the automatic calibration program at the initial stage.

2.2.2. Numerical optimization

PSO is selected as the algorithm used for the numerical optimization in this paper. This specific optimization technique was first proposed by Kennedy and Eberhart in 1995 [63,64]. The basic idea is to simulate the social behavior of a bird flock.

In the algorithm, the optimized solution for each issue is a bird – here typically called particles – in the search-space. Each particle has a fitness value determined by an optimized function and a velocity showing the direction and distance, searching in the solution space according to the optimizing particle. The particles are initially placed at random positions and finally find the optimized solution with the iterative method. In every iterative process, the particle updates itself by two vectors. The first one, called the personal best and represented by pBest, is the optimal solution found by this particle itself. The other one, called the group best and represented by gBest, is the optimal solution found by the whole group. In addition, the local best represents the optimal solution in its neighboring particles instead of the whole group.

The information of particle i can be denoted by a D-dimensional vector. The current position and velocity are X_i^t (X_{i1}^t, X_{i2}^t, ..., X_{iD}^t) and V_i^t (V_{i1}^t, V_{i2}^t, ..., V_{iD}^t), respectively, both of which are selected randomly at the initial stage and then iteratively updated according to Eqs. (10) and (11).

$$V_{id}^{t+1} = wV_{id}^t + C_1 Rand_1^t \left(pBest_{id}^t - X_{id}^t\right) + C_2 Rand_2^t \left(gBest_{id}^t - X_{id}^t\right) \tag{10}$$

$$X_{id}^{t+1} = X_{id}^t + V_{id}^{t+1} X \tag{11}$$

In Eqs. (10) and (11), d stands for the dimensions of the solution space. t is the iteration sequence. pBest is the personal best, the optimal solution found by the particle itself. gBest is the group best, the optimal solution found by the whole group. w is the inertia weight used to control the influence of the previous velocity on the current one. C_1 and C2 are the acceleration coefficients, adjusting the step-size of researching. Suitable C_1 and C_2 balance the convergence speed and the optimization effect. $Rand_1^t$ and $Rand_2^t$ are two uniformly distributed random numbers generated independently within [0, 1] for the dth dimension. The standard procedure of particle swarm optimization is illustrated in Fig. 3.

2.2.2.1. Optimization constraints.
There are some constraints in optimization problems of calibration because simulation models are built for practical applications, and the input parameters must be set to reasonable value ranges. These ranges heavily rely on the knowledge and experience of researchers and can be adjusted according to the calibrated results.

Apart from the fixed parameters of the software itself (such as the calculating method of heat and mass transfer), the input parameters can be divided into two categories:

1. Operational schedule. It contains set points of indoor temperature, on-off of lighting and equipment, etc. These parameters consist of a sequential set of data with highly varying randomness. The human behavior is characterized by particularity and instantaneity [65], so it is difficult to automatically calibrate
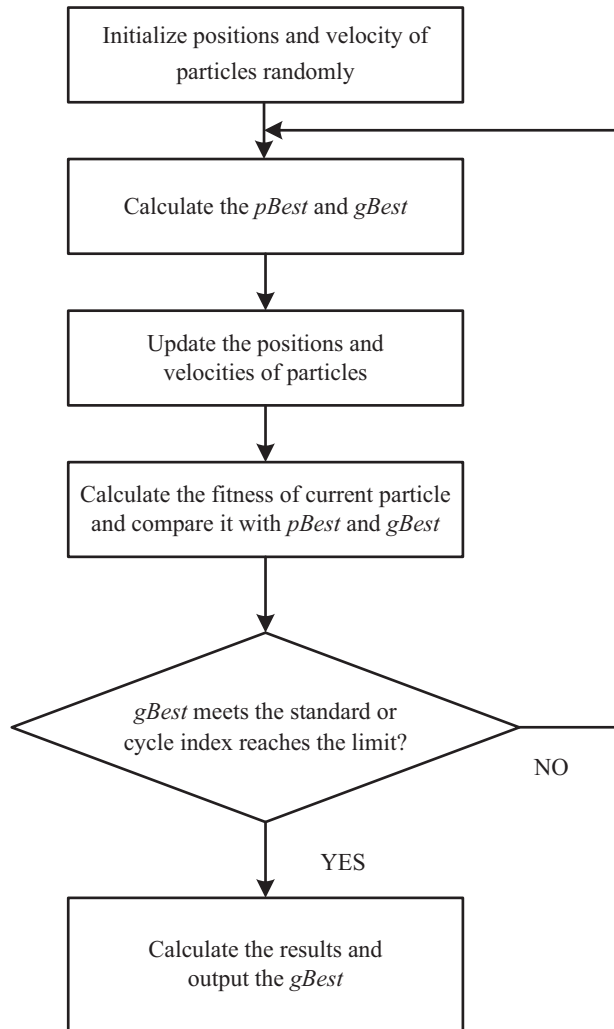
Fig. 3. Standard procedure of particle swarm optimization.

accurately. Therefore, in this paper, we fix the schedule with inputting the established parameters from the data of investigation and ASHRAE 90.1.
2. Physical and system features of buildings. This category includes transfer coefficients of the envelope, COP of chiller, etc. These parameters are the main research objectives and will be selected as the candidate list for optimization-based automated calibration in this paper.

Based on the sensitivity analysis, the information of the input parameters involved in the automatic calibration in this paper is shown in Table 8.

The range of parameters and the step size can be tuned according to the practical situation. Minimization of the number and the range of the tuned parameters lead to more accurate calibration results. In the extreme ideal situation, the proper narrow range of parameters will generate the unique objective solution. A longer step may result in a higher convergence speed but a lower accuracy of calibration, whereas a shorter step may result in higher accuracy of the calibration but a lower convergence speed. Therefore, the calibrated simulation must be properly performed to balance between the convergence speed and the calibration accuracy. The determination of step size in this paper refers to the accuracy of calibration and the convergence speed.

Table 8
Input parameters involved in the automatic calibration.

Parameters	Lower limit	Step size	Upper limit
External wall U-value [W/(m² K)]	0.30	0.10	1.50
Windows U-value [W/(m² K)]	1.50	0.50	6.50
Windows SC value	0.30	0.05	0.70
Lighting [W/m²]	5.00	2.00	25.00
Equipment [W/m²]	5.00	2.00	30.00
Occupant density [m²/p]	5.00	1.00	20.00
Pump efficiency	0.50	0.05	0.95
Chiller COP	3.00	0.50	6.00
Boiler efficiency	0.50	0.05	0.95
Fan efficiency	0.50	0.05	0.95
Fresh air [m³/(p h)]	20.00	3.00	40.00
Heating set point [°C]	16.00	1.00	24.00
Cooling set point [°C]	20.00	1.00	28.00

2.2.2.2. Optimization goal. The optimization goal is the objective function of the optimization algorithm to guide the direction of optimization and to determine the boundary conditions. This paper selects $CV(RMSE_{month})$ as the optimization goal to give an error criterion for iterative termination, as shown in Eqs. (3)–(5).

The objective function is illustrated in Eqs. (12), where f_{obj} means the objective function, $CV(RMSE_{total-elec})$ and $CV(RMSE_{total-gas})$ are the variation coefficient of the root-mean-squared error of the monthly total electricity and gas consumption respectively. The other similar variables, $CV(RMSE_{hvac})$, $CV(RMSE_{light})$, $CV(RMSE_{equipment})$ are also corresponding to the monthly electricity consumption of HVAC, light, and equipment. The values of $CV(RMSE_{month})$ can describe the data discreteness. Ki ($i = 1, 2, ..., 5$) are the weight coefficients of the corresponding objectives to determine which parameter will be optimized during the calibration using the objective function. Ki ($i = 1, 2, ..., 5$) ∈ [0, 1], and $K_1 + K_2 + K_3 + K_4 + K_5 = 1$.

$$f_{obj} = K_1 CV(RMSE_{total-elec}) + K_2 CV(RMSE_{hvac})$$
$$+ K_3 CV(RMSE_{light}) + K_4 CV(RMSE_{equipment})$$
$$+ K_5 CV(RMSE_{total-gas}) \tag{12}$$

2.2.2.3. Acceptable range for errors. One of the three ranges shown in Table 1 must be selected for calibration. This paper adopts CV (RMSE) in the ASHRAE-14 Standard as the assessment criterion.

In this paper, the development of an automatic calibration procedure adopts the ASHRAE-14 Standard by default. The tolerance range can be tuned in the following work. A decrease of the tolerance standard results in more accurate results from the calibrated model but requires a longer computation time.

2.2.3. Coupling of the optimization algorithm and energy simulation software

When the PSO algorithm is performed in the automatic calibration for building energy consumption, several loop iterations are needed to determine the solution for meeting the acceptable demand in the given range of input parameters. The optimization algorithm exchanges the data with the building energy simulation software (DOE-2) in every iterative computation.Each iteration loop includes the following steps:

(1) According to the previous error, the optimization algorithm program can produce an updated parameter group (random generation in the initial iteration);
(2) The updated parameter group is written into the input file, and then the new building energy model is established;
(3) Corresponding results are calculated, output and read through the energy simulation software. The deviation between actual and simulated data is then compared;

(4) The new error results are fed back to the optimization algorithm program.

The coupling approach is achieved using an external program. The optimization process and the DOE-2 calculation are relatively independent, but the input and output parameters may exchange and influence each other. Fig. 4 illustrates the schematic diagram.

When the optimization calibrated simulation is conducted, the following steps are included:

(1) The PSO algorithm randomly generates a particle swarm, and every particle represents an input parameter group;
(2) The external program updates the information of the "inp file" with the new data group and then creates a new "inp file";
(3) The computational core of DOE-2 is manipulated by the external program to load the new input file and simulate the new results;
(4) The external program reads the simulated energy consumption from DOE-2 and compares it with the actual one built beforehand. The error is calculated and then sent back to the PSO algorithm, which generates a new particle swarm.

This procedure loops until the error meets the demand or the number of iterations reaches the limit.

To realize this methodology, we compiled an external computational program, coupling the optimization algorithm and energy simulation software. This program is developed on C++, specific to the building energy simulation with the core of DOE-2. The interface is shown in Fig. 5.

3. Case Study

To verify the reliability and feasibility of the optimization-based automatic calibrated simulation program in this paper, we built a model using eQUEST for an existing building in Shanghai and used DOE-2 for the energy simulation.

3.1. Case description

The building, located in Shanghai, is 91.2 m high and has 19 floors above ground with a height of 4.8 m. The total area is approximately 20,780 m^2. The whole building utilizes an air-cooled heat pump for both space cooling and heating, with 10 °C cooling water temperature in summer and 38 °C heating water temperature in the winter. For the air supply part, a VAV system is adopted. Because the typical building discussed in the previous section is built on the basis of the investigation on tens of offices in Shanghai, which could basically contain and represent this given actual building, we apply the results of the aforesaid sensitivity analysis to this case study, and some important input parameters are set accordingly, as shown in Table 9.

The influence of the weather conditions on energy use should be ruled out. Because the actual electricity usage data of the building was measured in 2013, the typical meteorological year (TMY) weather data of Shanghai, in which the data of dry-bulb temperature and relative humidity are replaced by the corresponding real-time data in 2013, were used in the initial model run.

3.2. Initial results

After the initial simulation, the comparison of the total energy consumption data between the actual and simulated case is shown in Fig. 6. Some monthly errors were very high, larger than 10%, indicating the necessity of calibration.

3.3. Calibration process and results

Based on the established rule estimation, lighting and equipment densities can be calibrated by rule estimation, because the lighting and equipment densities directly change the electricity use, which can be easily identified. Other parameters may change the electricity use indirectly and may influence each other mutually, which is intricate for simple rules to calibrate. As presented in the results of the calibration programs, the lighting density should be tuned to 0.81 times the original data, and the tuning coefficient for the equipment density should be 0.87.

Figs. 7 and 8 depict the results of the rule-estimation calibration. For the lighting density, the error between the calculated and actual electricity consumption demonstrated a decrease of 7.3%. Meanwhile, a similar error decline of 7.2% was obtained for the equipment electricity consumption.

The results show that the calibration error in the section of lighting and equipment met the demand (less than 15%), but we cannot achieve a satisfactory result in the air conditioning part and hence the overall system. Thus, further optimization is required to achieve more precise calibration results. The PSO algorithm is used to calibrate all of the system parameters, except the lighting and equipment density. For the weight coefficients in the objective function, K_2 is set as 1, and the others are zero. The error criterion for iterative termination is set to 15%.

After four iterative calculations within one hour, the error of the electricity consumption in the air conditioning system was 11.6%, and the error of the total electricity consumption dropped to 6.1%. As a result, the errors of all four parts met the range of standard allowance using this approach.

The comparison of the monthly electricity usage of the total electricity consumption after the model optimization is shown in Fig. 9. Tables 10 and 11 show the errors of the end-use electricity data and the input parameters variation before and after calibration. The proposed automatic calibration program achieves good prediction accuracy.
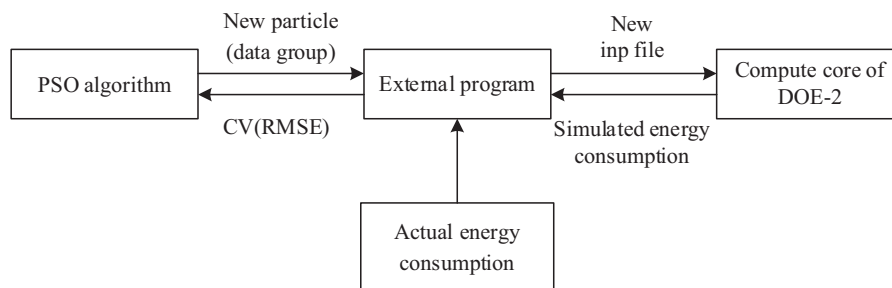

Fig. 4. Schematic diagram of the coupled optimization algorithm and simulation model.
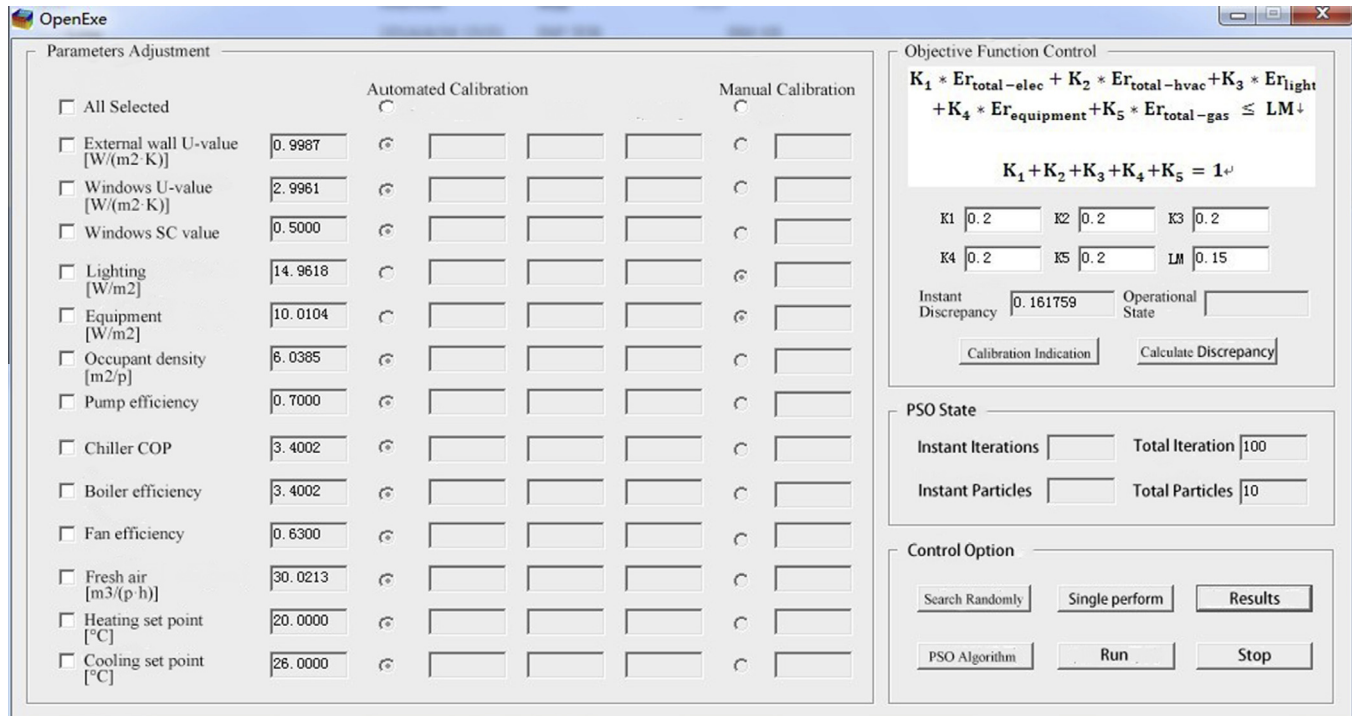
Fig. 5. User interface of the automated model calibration tool.

Table 9
Model input parameters.

| Category	Input parameters		Values
Envelope	External wall U-value [W/(m^2 K)]		1.00
	Windows U-value [W/(m^2 K)]		3.00
	Window SC		0.50
	Window-wall ratio	East	0.47
		South	0.29
		West	0.37
		North	0.29
Internal load	Lighting density [W/m^2]		15.00
	Equipment density [W/m^2]		10.00
	Occupant density [m^2/p]		6.00
HVAC system	Indoor set point [°C]	Heating Cooling	
		26.00 20.00	
	Fresh air [m^3/(p h)]		30.00
	Chiller COP		3.40
	Fan efficiency		0.63
	Pump efficiency		0.70
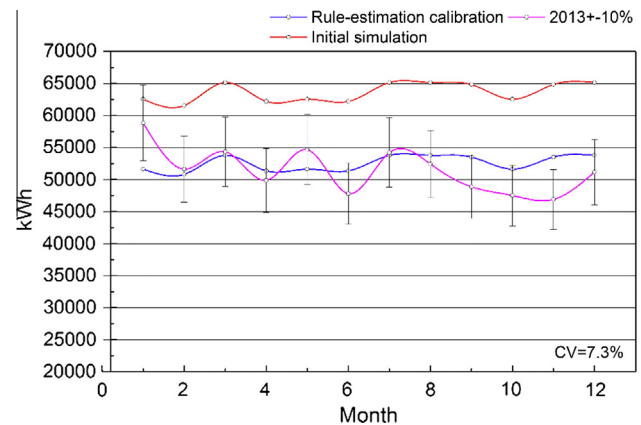
Fig. 7. Comparison of the simulated and measured lighting electrical usage in 2013 using rule-estimation calibration.

4. Discussion

This paper presents an inclusive automated optimization method for building energy simulation model calibration, which is developed on the sub-metering data. This methodology is compatible with some other advanced manual approaches. It could serve as a useful assistant for the experts to improve the efficiency of tuning relative input parameters. The novelty of this paper is elaborated as follows:

(1) The optimization-based automated calibration method presented in this paper is introduced to supplement and aid manual calibration by transforming the tuning process from the human brain to a computer to create a more efficient calibration that is less time-consuming. Because of the combination of various physical information and professional experience in manual calibration, this optimization
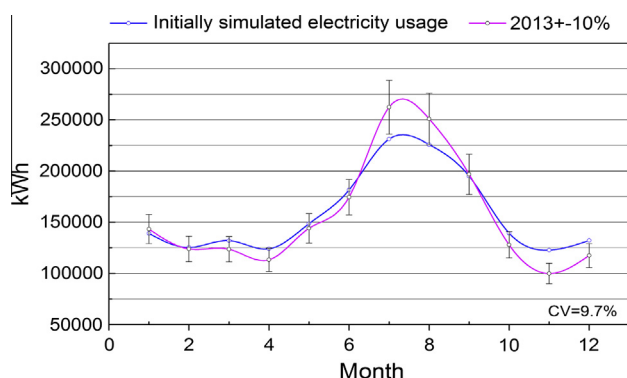

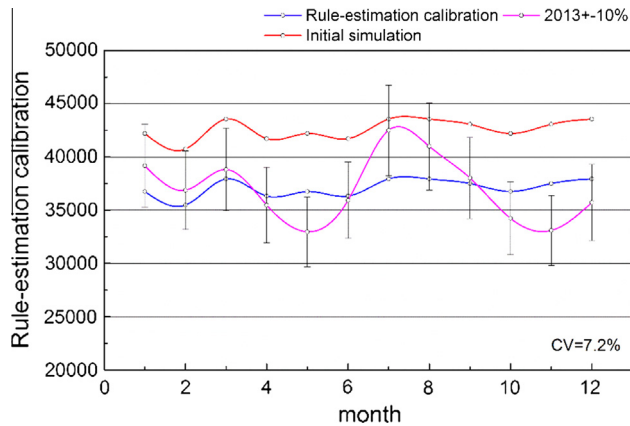**Fig. 6.** Comparison of the simulated and measured whole building electrical usage in 2013.

Fig. 8. Comparison of the simulated and measured equipment electrical usage in 2013 using rule-estimation calibration.
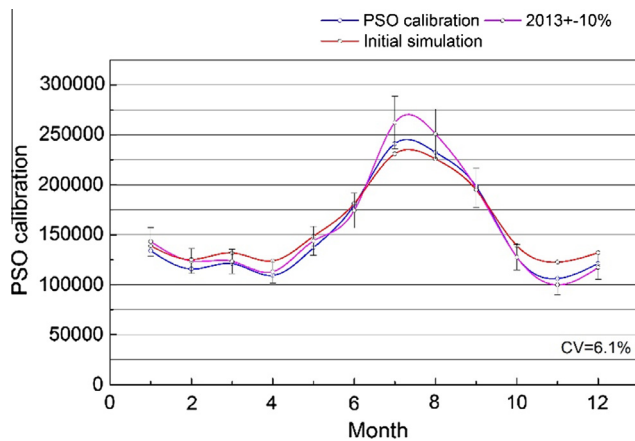

Fig. 9. Comparison of the simulated and measured whole building electrical usage in 2013 using PSO calibration.

Table 10
Model errors of each end-use before and after calibration.

CV (RMSE$_{month}$) [%]	Air conditioning	Lighting	Equipment	Total	Average
Initial model	29.90	24.60	16.80	9.70	20.20
Rule-estimation calibration	34.80	7.30	7.20	15.60	16.20
PSO calibration	11.60	7.30	7.20	6.10	8.00

Table 11
Model input parameters before and after calibration.

Parameters	Values	
	Before calibration	After calibration
External wall U-value [W/(m^2 K)]	1.00	1.35
Windows U-value [W/(m^2 K)]	3.00	4.80
Windows SC value	0.50	0.67
Lighting density [W/m^2]	15.00	12.20
Equipment density [W/m^2]	10.00	8.70
Personnel density [m^2/P]	6.00	9.30
Pump efficiency	0.70	0.90
Chiller COP	3.40	3.00
Heat pump efficiency for cooling	3.40	3.00
Heat pump efficiency for heating	0.63	0.82
Fresh air [m^3/(P h)]	30.00	40.00
Heating set point [°C]	20.00	23.20
Cooling set point [°C]	26.00	26.00

automated method, relying on mathematical and statistical techniques, cannot fully replace manual calibration. However, the advantages of automated calibration manifest in its efficiency and the accuracy of computers. To achieve its application, we compile an automated calibration program and perform it in a case study.

(2) Before implementing the optimization automated process, it is necessary to decide which parameters to tune and by how much, which we set it as "pre-processing". Apart from sensitivity analysis presented in this paper, this action makes full use of the modelers' domain knowledge, and specific methods in various given situations have been widely explored, such as a bottom-up calibration method based on hourly energy consumption data [19], a simultaneously calibrating framework on the multi-level [22], and a pattern-based approach [66]. Thus, the flexibility of pre-processing greatly expands the scope suitable for the optimization automated method.

(3) Because the fewer parameters the tuning process involves, the more effective the numerical optimization is, to guarantee the efficiency of the automated optimization method, the recommended number of input parameters is no more than 25 [28]. The pre-processing will alleviate this difficulty. The sensitivity analysis can identify the influential parameters to determine which can be tuned. This analysis is always developed based on several prototypical or actual buildings.

(4) With the improvement of the monitoring systems in buildings, the importance of sub-metered energy usage has emerged, which is an effective aid in making the calibrated model more accurate. Four types of main sub-items, including lighting, equipment, cooling, and heating, are investigated in this paper and could be simultaneously calibrated through a weighted function.

5. Conclusion and future work

In this paper, we propose an inclusive optimization automated approach to calibrate the building energy model with sub-metered data, and a detailed case is presented to illustrate this procedure. The result of calibrating the energy model for an actual building in Shanghai is that the electricity consumption from HVAC, lighting and equipment of the simulated model matches the actual monitored data with 11.6%, 7.3% and 7.2% CV (RMSE), respectively, and the total electricity consumption with 6.1%.

In contrast to previous studies, the intent of this paper is to explicitly orient the position of optimization automated approach in the calibration procedure. This automated optimization calibration is more likely to act as a supplementary method, rather than substitution, to optimize the existing manual calibration by the path of transforming manual adjustment to an automated process, thus greatly improving the accuracy and efficiency of calibration. Moreover, this inclusive methodology is greatly compatible with other advance manual calibration approach and assist the modelers in improving the efficiency of the tuning process. It is important to make the best of the advantages of efficiency and flexibility in the automated computer procedure, thereby avoiding the result of accurate mathematical matching but inaccurate physical matching. With a view to the increasing improvement of the monitoring system in buildings, another novelty of this paper is to present a creative method to consider the simultaneous calibration of four types of sub-items - lighting, equipment, cooling, and heating. More data measured from the monitoring system will contribute more to the fidelity of the building energy simulation.

During the entire calibration procedure, the pre-processing of determining which parameters to adjust and by how much before tuning can be completed by various other advanced manual

methods. The PSO algorithm is applied in this paper as an automated optimization method, but other techniques different from this adopted method could be applied to refine the parameters-tuning process. Furthermore, not restricted to the ERR or CV(RMSE) solely, some comprehensive weighted cost functions, including the responding weighted ratios, are worthy of more detailed research.

In spite of the merits in this proposed methodology, there exist still some problems to tackle. Firstly, the operational schedule is not considered into the process of automated calibration. We fix it manually now, as accurately as possible based on the general design standard and investigation information. Besides, this process tends to be a deterministic approach to search a single set of best-fitting parameters. The drawback is the limited final targets of optimization, unable to cover all the uncertain bounds of the given model. To solve this problem, Bayesian calibration [67] could be introduced in the "post-processing" in the future studies.

Overall, despite these limitations, the mathematical optimization-based automatic calibration method has a significant advantage in the specific parameters-tuning process. With the convenience of computer program, it could assist the modelers in improving the efficiency of the tuning process. For its limitations, as long as we implement some auxiliary methods, including sensitivity analysis and Bayesian calibration, into the building energy simulation calibration, the deficiency of the optimization method will be effectively eliminated in future works.

Acknowledgements

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