A novel concept to measure envelope thermal transmittance and air infiltration using a combined simulation and experimental approach

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Highlights:

1. A novel method for measuring envelope U-values and air infiltration is proposed.
2. The proposed method considers building heat losses in a quasi-steady state to eliminate uncertainties caused by dynamic energy consumption resulting from occupant behavior.
3. A regression model is used to reduce computational processing time in optimization process.
4. Through calibration, simulated heat consumption matches well with measured data.

Abstract

This paper presents a novel method to determine building envelope thermal transmittance (known as U-values) and air infiltration rate by a combination of Energy modeling (DesignBuilder and EnergyPlus), regression models and genetic algorithm at quasi-steady state conditions. DesignBuilder is used to develop the thermal model of an office building, including physical building models, materials specification, occupancy schedules, detailed HVAC system and components for energy simulation purposes. Specifically, the simulation was carried out in EnergyPlus at diverse U-values and air infiltration rates to produce a large datasets. Subsequently, the results were used to generate a linear regression model to evaluate the associations of thermal demands with U-values and air infiltration rate. Genetic algorithm was then applied to obtain a set of U-values and air infiltration rate with the minimum difference between field measurement and model prediction. The calibrated U-values and air infiltration rate were employed as inputs in EnergyPlus to model one workday heat consumption. When compared with thermal demand from measured data, the accuracy of the calibrated model improved significantly.

Key words: U-values; air infiltration rate; energy modeling; regression models; genetic algorithm

1. Introduction

The Building sector is responsible for 40% of energy consumption in Europe [1]. Buildings in Europe have a lower thermal performance due to the fact that a high percentage were constructed before 1960s when thermal resistance of envelopes was poorly regulated, and have not undergone refurbishment to replace their old systems or to enhance their envelopes with insufficient or without insulation [2] and [3]. With the urbanization and increased comfort standards, energy demand is expected to keep growing [4] and [5]. In response to the present energy and environmental issues, the reduction of energy consumption form the key challenge in building area, in particular, the heating and cooling energy demand. The thermal transmittance (U-value) of envelope and the air infiltration rate are the most critical aspects from a thermal performance perspective. As a result, determination of envelope thermal properties and air infiltration are essential for energy modeling.

Envelope U-values rely on several factors, such as envelope surface roughness, air flow pattern and wind speed. Thermal losses from building surface account for a large proportion of respective thermal balance [6]. Field U-value measurement is normally fulfilled through heat flux. Temperature sensors and heat flux sensors are attached to both sides of a building element to measure temperature and heat flux respectively at a steady state. In order to obtain an average value of the whole building, this process is replicated in several locations, which is time consuming and involves repetitive tasks with a substantial cost implication. If the wall or roof is not homogeneous, thermal bridges should be considered. The heat losses affected by thermal bridges should be measured separately to obtain validated U-values [7]. Meanwhile, Users may easily affect the precision and bias of the results. Even with the same operator and the same equipment, the results still can differ due to measurement uncertainty [8]. Alternatively, U-value not influenced by thermal bridging can be obtained through theoretical calculation using equation (1) by knowing the thermal resistance of each layer that constitutes the envelope and its inside and outside surface thermal resistances.

$$\mathrm{U-value} = \frac{1}{\sum R + R_i + R_o} \quad (1)$$

When the influences of buildings thermal bridge are considered, this value should be multiplied by an incidence factor to obtain a validated U-value [9].

Interest in air permeability in building envelopes has increased, owing to the increasing concern about building energy performance and indoor environmental quality [10] and [11]. Air infiltration is generally defined as the unexpected or accidental introduction of air from outdoor into a building. Building thermal performance requires restricted envelope airtightness, especially when designing low carbon buildings. However, sufficient air exchange is also recognized as essential to enhance airflow circulation and ensure indoor thermal comfort. Many researches are devoted directly to measuring air infiltration rate on-site, which is usually measured through two typical methods: (1) Tracer gas equipment to trace concentration values of inert gas; or (2) fan pressurization method at a pressure difference of 50 Pa. For the former, given the stratification of tracer gas, it is impossible to obtain a uniform concentration within the building [12]. The later could not be used to evaluate the airflows at natural conditions. Uncertainties of current empirical assessment impact the accuracy of building performance evaluation [13]. A wrong evaluation of the air infiltration can result in the oversizing of the ventilation system [14].

Existing publications related to building energy assessment are mostly based on simulations and experiments. Energy simulation is widely used given its practicality in energy profiling of a building. Meanwhile, In situ measurement as discussed involves big uncertainty resulting from devices accuracy and user intervention. Valuable works have been published related to building simulation calibration which highly contributed to the fidelity of simulation models [15] [16] [17] [18] and [19]. The purpose of these calibrations is to determine the appropriate parameters that are most sensitive to energy consumption, some focusing on specific variables and some focusing on all the determinants. Human related activities are involved in the calibration process. The credibility of the calibrated variables is questionable since they are easily affected by some difficult to measure variables such as human related behaviors (e.g. door and window openings and human activities) [20]. Research revealed that human behavior can result in up to 50% higher heating demand and further investigation on this aspect should be carried out in order to precisely predict users heat load profile through simulations [21].

Evidences suggest that existing approaches for determining U-values and air infiltration rates are time consuming and not fully reliable. To address this gap, the present study introduces a novel method to calibrate U-values and air infiltration rate through simulation and experimental measurements. To the best of our knowledge, no one has done research to separate the effect of human related factors from other parameters. DesignBuilder and EnergyPlus are used to construct the simulation model for the building, setting up the input variables, schedules, detail HVACs and running the simulation. A number of datasets were obtained to investigate energy consumption of different zones for a single day under different circumstances. Regression models were established to replace EnergyPlus model for simulation purposes. Subsequently, GA will be briefly introduced. A fitness function to evaluate the gap between the measured and predicted heat consumption was presented to search for the most appropriate U-values and air infiltration rate. Finally, a simulation with human activity involved was carried out and the results benchmarked with measured data.

2. Related work

Building heat consumption is an important element to evaluate the effectiveness of an entire building. The main driving forces for heat consumption are building surface heat loss, air infiltration, domestic hot water, window and door openings and mechanic ventilation, which can be concluded as:

$$Q_{consumption} = Q_{envelope} + Q_{Infiltration} + Q_{DHW} + Q_{openings} + Q_{mechanic\ ventilation} \tag{2}$$

When evaluating the thermal performance of a specific building, it is necessary to exclude the influence of human related heat consumption coming from domestic hot water, opening and mechanic ventilation. The formula (2) can be simplified as:

$$Q_{consumption} = Q_{envelope} + Q_{Infiltration} \tag{3}$$

Heat loss through building envelope is caused by the temperature deviation between interior and exterior. Indoor temperature is relatively stable at a constant set temperature to meet the requirement of occupant thermal comfort. Outdoor temperature varies with local weather conditions. However, as the weather evolution is slow, the whole process can be regarded as a quasi-steady state. A quasi-steady state is similar to a steady state, which is generally applied to reduce system dimensions and to make problems more tractable, especially in reduction of parameters for identifying problems. The heat loss through exterior wall, window, roof and floor can be described as:

$$Q_{window} = \int_0^t U_{\mathrm{window}} * A_{window} * \Delta T \tag{4}$$

$$Q_{exterior\ wall} = \int_0^t U_{\mathrm{exterior\ wall}} * A_{exterior\ wall} * \Delta T \tag{5}$$

$$Q_{roof} = \int_0^t U_{\mathrm{roof}} * A_{roof} * \Delta T \tag{6}$$

$$Q_{floor} = \int_0^t U_{\mathrm{floor}} * A_{floor} * \Delta T \tag{7}$$

Where, t is the time duration. U_{window}, $U_{exterior\ wall}$, U_{roof} and U_{floor} denote U-values of window, exterior wall, roof and floor respectively. And those U-values include the effect of thermal bridges. A_{window}, $A_{exterior\ wall}$, A_{roof} and A_{floor} are the areas for windows, exterior wall, roof and floor. ΔT is the temperature difference between indoor and outdoor.

Apart from the thermal loss through building envelope, another implication to heat consumption is the air leakage. Warm indoor air that leaks out of the building carries some heat, resulting in more heat demand. Heat consumption caused by air leakage can be quantified by:

$$Q_{infiltration} = \int_0^t C_p * \rho * Q * \Delta T \tag{8}$$

Where, C_p is the specific heat of air. ρ is the density of air. Q is the volume of air exchange rate.

Building performance simulation is an established method to understand building energy demand. It has been applied to analyze energy performance at design, retrofit and operation process, which facilitates the reduction of a great deal of capital and labor investment when compared with experiments. Nowadays, high-performance buildings depend heavily on validated models as simulation tools are available for parametric studies in order to choose the optimal solution from structural, material and operational schemes. A great effort has been devoted to sensitivity analysis of input variables to improve the quality of energy simulation, which provides information about how buildings react to various parameters when a given parameter is altered [22] [23] and [24]. Those studies are important steps towards improving the accuracy of simulation by better accounting various parameters as input variables. The sensitivity study are mostly based on the scenario study to examine the influence of occupancy, orientation, materials and control technology, which is often impractical and not completely reliable if the non-linear interaction among input variables are involved [20]. Evidences suggest that Building occupants highly affect building energy consumption [25] and [26], forming the main cause of discrepancy between simulation and measured data. Despite the advanced abilities of building simulation tools such as EnergyPlus, IES and eQuest, they typically fail to quantify the impact of uncertainty in human activities such as occupancy and interaction with building elements (e.g. openings), resulting in substantial prediction errors [27]. This is also another reason why human related activities should be eliminated from the system. Isolating occupants' activities should greatly improve the simulation accuracy.

Regression models have been widely employed to understand energy usage in buildings, as it is computationally expensive to run all possible simulations in building simulation tools. The major merits of regression methods are that they are comparatively simple and efficient. They allow the establishment of relationships among inputs and outputs for computation within the shortest time. Kavousian et al. [28] examined the impact of climate, building characteristics, appliance stock and occupants' behavior on residential electricity consumption based on history data by a weighted regression model. Walter and Sohn [29] developed a multivariate linear regression model to predict energy saving at multiple alternative retrofit options. Yuce [30] adopted linear equation derived from simulation and sensitivity analysis in EnergyPlus to predict energy generation. Yin [31] estimated residential and commercial building demand response by using regression models to fit dataset. Wang et al. [32] explored variables' sensitivity in EnergyPlus by using a stepwise regression method.

3. Methodology and case study description

3.1 Experimental study

This section summarizes the studied building used as a basis to implement the proposed method. The test was performed in a two-story old office building in south wales, built in 1915. The building was refurbished in 2011 to meet the requirements displayed in Table 1. The targets do not always match with the true values as a result of the aging process and installation features.

The heat consumption in this building is higher than predicted. The building is currently occupied by Blaenau Gwent Borough Council Office, the Gwent Archives and Ebbw Vale Works Museum. The office and museum zones open from 9:00am to 17:00pm during workdays. The archives open from 9:00am to 17:00pm daily. The heating system in the office zone and museum zone run from 7:00am to 17:00pm workday and the archives run 24 hours. The archives zone is heated based on 24 hours 7 days a week. The exact structure and materials for the building is provided by the company who is responsible for the refurbishment.

Table 1 Targets of refurbishment in 2011

Air infiltration (ACH)	External Walls U-value (W/m^2K)	Roof U-value (W/m^2K)	Ground Floor U-value (W/m^2K)	Window U-value[1] (W/m^2K)
0.25～0.5	0.35	0.25	0.25	2.2

[1] The exterior door was described as a window; ACH = air change per hour

Smart meters were deployed in different zones after retrofit and are accessible for data collection. As the foresaid description, the interference of human related heat consumption, caused by opening, mechanical ventilation and domestic hot water, should be eliminated. The experiment was performed on Sunday and no human activity was involved. The heating system did not shut down on Friday after work and kept on operating to ensure that the building could achieve a quasi-steady state on Sunday. Heat consumption data for that day were gathered, which will be used for the following study.

3.2 Numerical study

The simulation study in this paper was carried out in EnergyPlus, which is one of the most reliable tools used for energy analysis in the field of simulation-based optimization. It can be used to simultaneously model building loads, HVAC and other associated components and has been accepted as a powerful tool for building energy simulation [33] [34]. This calibration simulation is purely based on the easy to find parameters such as geometry, orientation, construction materials, heating set point temperatures and outdoor weather conditions.

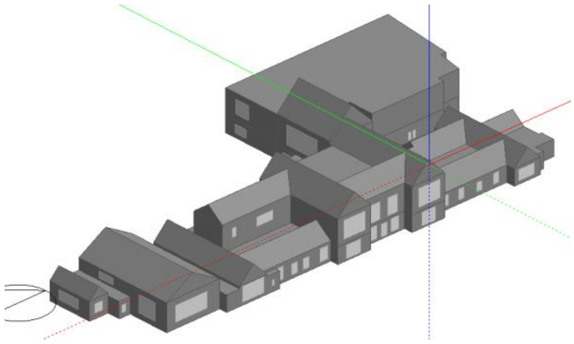

Fig. 1 structure of the general office

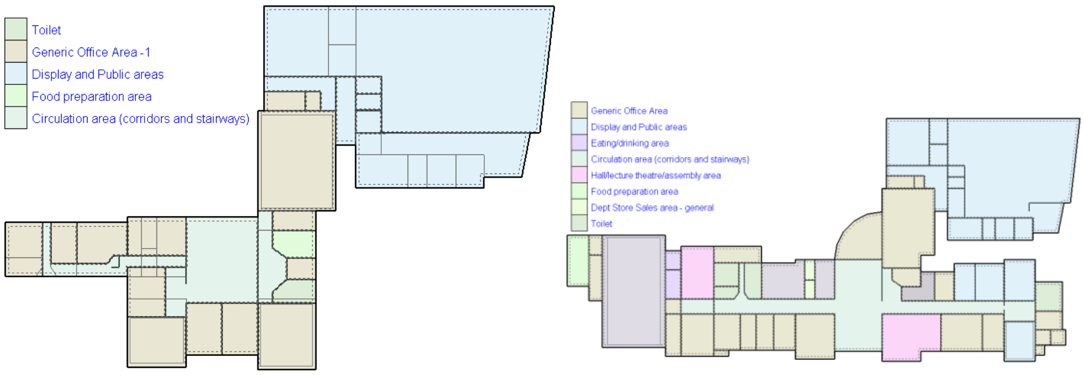

Fig. 2 plan view of first floor (left), ground floor (right)

In this study, DesignBuilder was firstly used to develop the physical model of the whole building from plans as shown in Fig. 1. This includes geometrical information, building materials details, a detailed description of the HVAC system and HVAC schedules. The building was partitioned into 19 different thermal zones based on the installed heat meters, function (office, toilet, archives, kitchen etc.) as shown in Fig. 2, and set point temperature. The model was then exported into EnergyPlus for further computational simulation, which was applied to develop a mathematical model to identify thermal performance of the building. Weather data from a nearby weather station was collected and converted to EnergyPlus readable (epw) file. Eventually, EnergyPlus calculated the heating demand at a specified day in line with the focus of the experiment. 47 set of simulations were conducted in EnergyPlus under various design U-values of the wall, roof, floor and window and air infiltration conditions, listed in Table 2. Convective heat transfer balance algorithm adopted for inside surface is TRAP model, while DOE-2 model is used for outside surfaces [35].

Table 2 different design air infiltration rates and design U-values applied in the simulation

	Infiltration	Wall	Roof	Floor	Window

	(ACH)	(W/m2K)	(W/m2K)	(W/m2K)	(W/m2K)
1	1.25	1.524	0.27	0.257	2.25
2	1.25	1.366	0.31	0.313	2.24
3	1.25	1.121	0.38	0.412	2.25
4	1.25	0.846	0.45	0.46	2.26
5	1.25	0.761	0.53	0.549	2.26
6	1.25	0.925	0.45	0.504	2.26
7	1.25	0.801	0.72	0.449	2.26
8	1.25	0.34	1.09	0.545	2.25
9	1.25	0.393	0.31	0.389	2.18
10	1.25	0.409	0.59	0.358	2.21
11	1.25	0.183	0.18	0.072	1.99
12	1.25	0.141	0.13	0.069	2.13
13	1.25	0.141	0.05	0.132	0.95
14	1.25	0.099	0.06	0.282	1.77
15	1.25	0.078	0.22	0.166	1.54
16	1.25	0.052	1.35	1.122	2.27
17	0.75	1.524	0.27	0.257	2.25
18	0.75	0.601	0.32	0.314	2.25
19	0.75	0.846	0.44	0.425	2.27
20	0.75	0.409	0.72	0.564	2.27
21	0.75	0.071	0.25	0.099	2.29
22	0.75	0.052	0.05	0.059	0.95
23	0.75	0.123	0.21	0.083	1.33
24	0.75	0.148	0.16	0.135	1.99
25	0.75	0.052	0.06	0.037	1.54
26	0.5	1.524	0.27	0.257	4.01
27	0.5	0.764	0.16	0.064	4.11
28	0.5	0.052	0.05	0.059	1.18

29	0.5	2.33	2.72	1.479	2.74
30	0.5	1.366	0.18	0.32	3.29
31	0.5	1.121	0.35	0.559	3.92
32	0.5	0.876	0.34	0.545	2.74
33	0.5	0.725	0.05	0.081	1.83
34	0.25	1.524	0.27	0.257	5.76
35	0.25	0.846	0.09	0.203	5.07
36	0.25	0.541	0.31	0.526	1.29
37	0.25	0.104	0.08	0.081	2.12
38	0.25	0.071	0.05	0.542	2.7
39	0.25	0.099	0.09	0.404	2.12
40	0.25	0.514	0.59	0.296	2.12
41	0.15	1.524	0.27	0.257	5.76
42	0.15	0.236	0.34	0.25	1.29
43	0.15	0.114	0.08	0.07	2.12
44	0.15	0.071	0.31	0.296	2.7
45	0.15	0.365	0.31	0.367	3.13
46	0.4	1.524	0.27	0.257	5.76
47	1.5	1.524	0.27	0.257	5.76

3.3 Regression model

After the simulation stage in section 3.2, the computed heat consumption of the 19 thermal zones can be obtained at different inputs. The SPSS software was used for linear regression to find out the relationship between different inputs and heat consumption. The generalized formula of the multivariate linear regression model with 5 indicator variables is as follows:

$$Q = a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5 \tag{9}$$

Where, Q denotes simulated heat consumption. X_1, X_2, X_3, X_4 and X_5 represent the input variables such as air infiltration and U-values for wall, roof, floor and window. a_0, a_1, a_2, a_3, a_4 and a_5 are the regression coefficients.

3.4 Calibration method

For a quasi-steady state without the involvement of human activities, the most important parameters for heat loss are the aggregated envelope U-values and air infiltration rate. The process of calibration is the procedure for searching the optimal variables to verify the elaborated models. The decision parameters requiring calibration in this section are U-values and air infiltration rate.

Fig. 3 depicts the process of optimization and regression analysis used for implicit calibration. The possible parameters are fed into the regression model to predict thermal demand. The optimization tool then adopts an evaluation function to limit the discrepancy between heat consumption data collected from the test period and predicted value. The ability of a mathematical model to precisely predict thermal conditions relies on the validity of the associated model parameters.

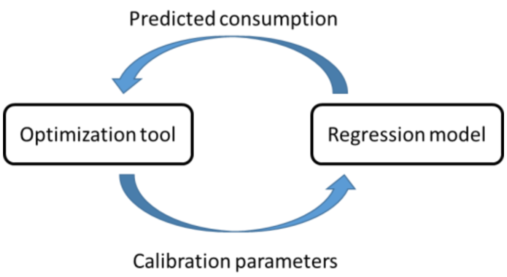

Fig. 3 Implicit Calibration

The optimization tool adopted in this paper is genetic algorithm (GA), which is a popular search heuristic algorithm derived from biological evolution. It has been used in mathematics to mimic natural evolution in the process of optimization. It can be applied for both constrained and unconstrained optimization. The whole process for optimization can be described as [36]: GA generates an initial population of chromosomes. It then assesses the fitness of each chromosome and selects the best individuals to produce their offspring in each iteration. The offspring are produced by crossover and mutation of the parent generation. The best ones of each generation have the highest possibility of generating the next generation. Generally speaking, GA cannot ensure the ultimately best solution will be achieved. However, it can produce a near-optimal solution.

The utilization of GA here is to figure out the real values for X_1, X_2, X_3, X_4, X_5 with the minimum difference between measured data from the site and predicted value from the regression models. The constraints of the decisive variables, air infiltration and U-values, are set according to the design values, as shown in Table 3. The true values can both be better or worse than the design values. It should be noted that the U-values of the building vary with temperature and moisture content. In reality, the values of the parameters might be in a great range as the aging and corrosion processes. For the purpose of covering a wide range of potential values in real operation and also taking into account the design values, the true values for air infiltration and U-values should satisfy the requirements in Table 3, where the lower bound and upper bound are the possible minimum and maximum values for the variables.

Table 3 variation range of the variables

	Lower bound	Upper bound
X_1	0.05	2
X_2	0.025	2.5
X_3	0.025	2.5
X_4	0.025	2.5
X_5	0.2	10

The most important part of the GA is to define the fitness function. Researches reveal that the discrepancies between model prediction and real performance mainly result from the differences between initial design and actual operation [16], [37] and [38]. The objective function here is to minimize the difference between simulation and measured heat consumption in order to find the real values. The fitness function is addressed as:

$$\text{Min f(x)} = \sum_{n=1}^{19}(Q_{ns} - Q_{nm})^2 + (Q_s - Q_m)^2 \quad (10)$$

Q_{ns}, Q_{nm}, Q_s, $Q_m$are measured heat consumption of individual zone and whole building.

The overall process of the methodology in this paper is depicted in Fig. 4.

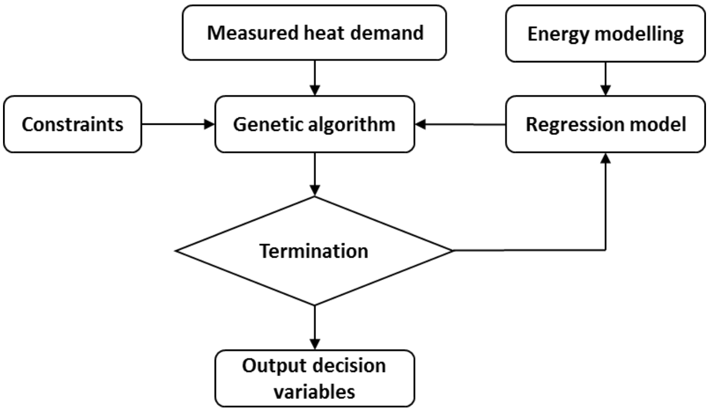

Fig. 4 Flow chart of the research methodology for the this paper

4. Results and discussion

4.1 Regression validation results

After simulation under 47 sets of different inputs, heat consumption of different zones were obtained. The 47 simulation instances were applied to train the regression model. As the limitation of space, 6 zones and the whole building were selected to analyze the regression model. The fitted regression models for each zone are listed as follows:

$$Q_1 = -3.751 + 239.108 * X_1 + 111.77 * X_2 + 127.311 * X_3 + 43.75 * X_4 + 4.899 * X_5 \quad (11)$$

$$Q_2 = 3.041 + 137.868 * X_1 + 83.337 * X_2 + 52.666 * X_3 + 28.611 * X_4 + 13.867 * X_5 \quad (12)$$

$$Q_3 = -18.112 + 90.449 * X_1 + 47.95 * X_2 + 34.695 * X_3 + 18.084 * X_4 + 11.368 * X_5 \quad (13)$$

$$Q_4 = -0.849 + 53.405 * X_1 + 77.821 * X_2 + 7.189 * X_3 + 159.323 * X_4 + 3.327 * X_5 \quad (14)$$

$$Q_5 = -15.046 + 101.484 * X_1 + 55.591 * X_2 + 49.179 * X_3 + 124.894 * X_4 + 12.639 * X_5 \quad (15)$$

$$Q_6 = -1.039 + 3.253 * X_1 + 2.762 * X_2 + 3.5 * X_3 + 8.971 * X_4 + 0.767 * X_5 \quad (16)$$

……

$$Q = -195.447 + 1239.142 * X_1 + 742.934 * X_2 + 579.198 * X_3 + 998.006 * X_4 + 121.642 * X_5 \quad (17)$$

Where Q_1, Q_2, Q_3, Q_4, Q_5, Q_6, Q denote heat demand for zone 1, zone 2, zone 3, zone4, zone 5, zone 6 and the whole building, respectively.

The objective of the linear regression model is to obtain an efficient and accurate model to predict heat consumption for each zone at different inputs as the building energy performance simulation tool EnergyPlus is time consuming. The predicted values for thermal consumption derived from the fitted regression models are compared with the simulated data from EnergyPlus. More specifically, the predicted heat consumptions are calculated from the linear regression model by taking inputs corresponding to the independent variables into the above equations (e.g. U-values and air infiltration rate). The simulated values from EnergyPlus and computed data from regression model were compared as shown in Fig. 5.

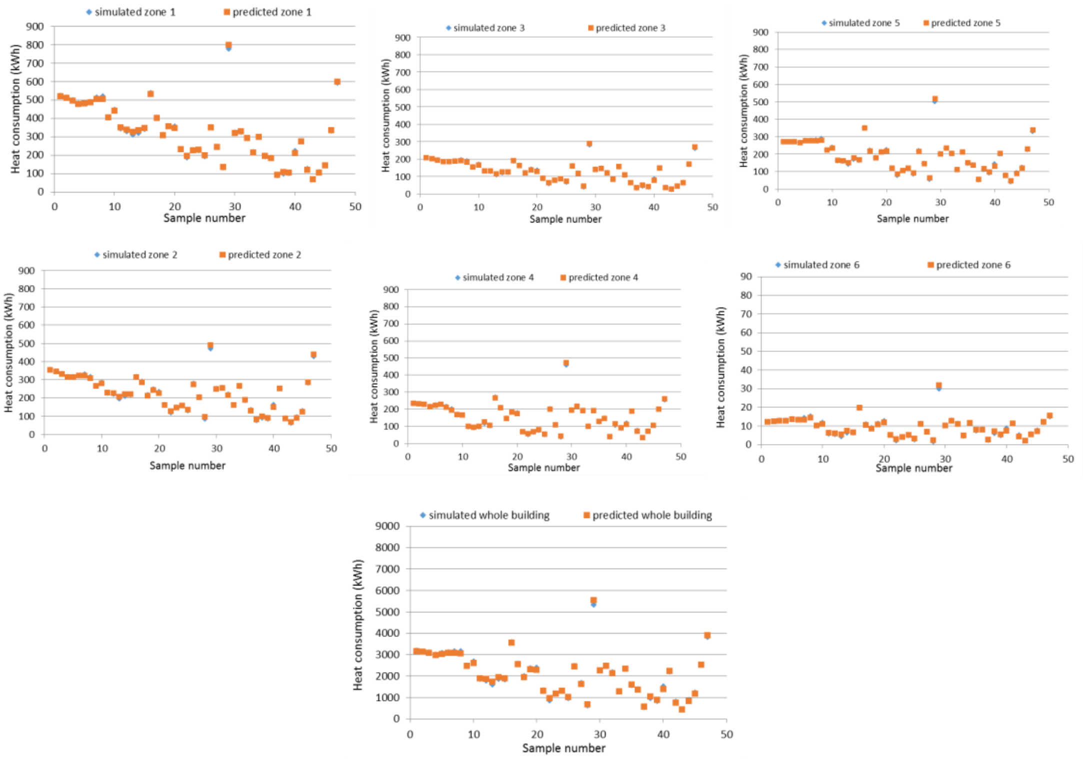

Fig. 5 simulated and predicted heat consumption of zones

Following the development of regression models, the regression models' fitting and predicting ability of thermal energy demand is evaluated. The goodness of the regression model can be verified by Normalized Mean Bias Error (NMBE) and Coefficient of Variation of Root Mean Square Error CV-RMSE [39].

Error	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Whole building
NMBE (%)	-4.6e-4	-4.7e-4	1.1e-3	6.1e-5	-3.2e-4	-5.2e-5	-1.7e-3
CV-RMSE (%)	2.0	2.9	3.1	2.8	3.0	6.7	3.0

The equations used for calculation are as follows:

$$\text{NMBE} = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{(n-p) * \bar{y}} * 100 \quad (18)$$

$$\mathrm{CV-RMSE} = \frac{\sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{(n-p)}}}{\bar{y}} * 100 \tag{19}$$

ASHRAE Guideline 14 points out that “The computer model shall have an NMBE of 5% and CV (RMSE) of 15% relative to monthly calibration data. If hourly calibration data are used, these requirements shall be 10% and 30%, respectively” [40]. The NMBEs and CV-RMSEs displayed in the table are relatively low. Therefore, from the statistical point of view, we confidently conclude that the regression model can be used to predict heat consumption at a quasi-steady state without human action interference.

4.2 Main results of validated values

After generations of selection, crossover and mutation in GA, the final values were obtained (shown in Table 4), which would result in a minimum difference between predicted data in regression models and measured data from the site. The validated results are worse than the design values, which indicate the building is operating in a bad condition.

Table 4 validated air infiltration rate and U-values

Air infiltration (ACH)	External Walls U-value (W/m^2K)	Roof U-value (W/m^2K)	Ground Floor U-value (W/m^2K)	Window U-value[1] (W/m^2K)
0.727	0.678	0.385	0.356	2.416

4.3 Simulation result

The limitation of this work lies in that the authors did not carry out the field measurement to obtain the U-values and air infiltration rate. In order to validate the proposed calibration method, the predicted heat consumption from calibrated energy simulation model and measured data for a typical workday was demonstrated. A detailed occupancy and a detailed HVAC system were included in the simulation. The uncalibrated model based on design values was also displayed as a comparison.

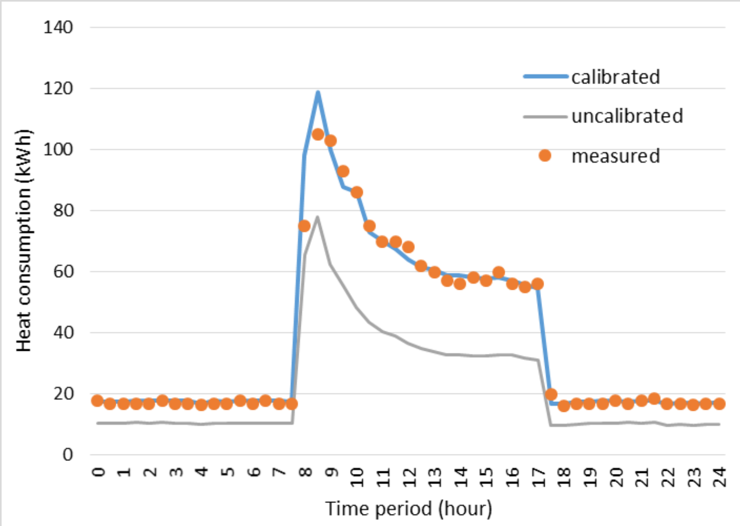

Fig. 6 Calibrated results compared with measured and uncalibrated data

Fig. 6 displayed heat consumption for every half hour. It can be seen that a great discrepancy exists between calibrated and uncalibrated models. For the uncalibrated, the u-values and air infiltration rate are lower than the calibrated model, which results in less energy demand. It is obvious that the accuracy of the calibrated model improved significantly. The calibrated model showed good agreement with the measured data at night. Even though a small difference between the measured and predicted model during the day is found, it is acceptable and this may be caused by the embedded thermal bridges and the unpredictable human activity.

5. Conclusion and future work

Measuring building envelope U-values and air infiltration is complex as the empirical technology is difficult to implement and involves a wide range of uncertainties. Meanwhile, the whole process usually takes a large amount of time, man efforts and is costly. In this paper, we proposed a novel concept to obtain the U-values and air infiltration by using those easy to obtain parameters. The proposed method considers building heat losses in a quasi-steady state to eliminate uncertainties caused by dynamic energy consumption resulting from occupant behavior.

This computational approach combined with field gathered data calibration could serve as an alternative to traditional methods. It can also act as a supplementary method for parameter sensitivity analysis of building performance simulation to increase accuracy by reducing the number of variables needed during the process of calibration. The advantages of this method are that it is easy to implement and can be used for any building. It does not require any sophisticated devices and simply requires a personal computer and access to existing meters in the building. The process and related time necessary to determine the U-values and air infiltration are several times shorter than the traditional methods. The accuracy and reliability of the simulation can be further improved by choosing an appropriate indoor and outdoor heat convection models.

The method introduced in this paper is replicable and can be used for any building regardless of its geographical location and orientation. Future work will involve further field tests and evaluation to stress-test the proposed method and analyze the U-values under different weather conditions. As the weather conditions will affect the humidity of the envelope, the U-values will be different under four seasons. The calibrated values can be applied to precisely predict heat consumption from simulation or to provide guidance for retrofitting of existing building.

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