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Calibration of the Energy Simulation Model of a Library with a Meta-Model-Based Optimization Approach

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Abstract

Building simulations play a fundamental role both in applications like the design of new constructions and the optimization of building operation and control. This is quite relevant in the current energy framework, in which the energy consumption of buildings has increased over past decades. The reliability of the results' model does not depend only on the model itself, like the mathematical expression or the resolution process, but it is also related to the uncertainty that those parameters involve. This can cause discrepancies between the simulated and the real behavior of the building, causing a deviation from the expected one of the performance of a building. Hence, the calibration procedure of the model is a necessary process which allows more accurate results to be obtained and predictions that are closer to the real behavior of the building to be made, minimizing the discrepancy between predicted and actual performance by changing the values of the simulation parameters. When it comes to calibration of simulation models, many approaches are available in the literature, comprising manual and iterative ones, graphic comparative procedures, techniques based on specific tests, and many others. Among all possible approaches, optimization-based calibration is the most widely adopted in model calibration. However, this approach, which is usually based on evolutionary algorithms, has the disadvantage that it requires many expensive simulations to be run, especially when the number of parameters to be calibrated is high. This issue can be overcome by a preliminary sensitivity analysis that reduces the number of parameters to be calibrated and by an efficient optimization algorithm. For this reason, this work proposes a framework based on a sensitivity analysis designed to identify the most significant parameters separately on the energy budgets and other monitored environmental variables. The proposed calibration procedure is based on functional approximation models, which greatly increases the efficiency of the optimization algorithm. The case study is a university library placed in the municipality of Trento, Italy. The building was monitored in terms of indoor carbon dioxide, indoor temperature, and relative humidity. Results show how successful the proposed approach is in reducing the computational time required for calibration, especially when considering models with a high degree of complexity.

1. Introduction

Energy demand from buildings is still considered a significant share of the global energy consumptions, i.e., 36 % of the total energy demand (Santamouris & Vasilakopoulou, 2021). This means that measures in this sector must be taken to considerably reduce overall energy consumption. In this context, dynamic simulations of buildings are an extremely powerful tool, which can help in achieving such goals, not only from the point of view of assessing the energy efficiency of new constructions, but also for optimizing building operation and control. Nevertheless, dynamic and detailed models require a high number of both input data and parameters for describing the whole system. As reviewed by Chong et al. (2021), the building model requires input data which describe the physical model. If not directly measured or known, as in the case of new constructions, parameters must be assumed by the user. This assumption procedure brings uncertainty that has an unavoidable impact on the simulation output. Authors such as Karlsson et al. (2007), Scofield (2009) and Turner & Frankel (2008) reported how simulation results can differ significantly from monitored data. Hence, to adopt energy models that are as accurate as possible, calibration procedures are becoming increasingly fundamental and are an unavoidable step in building simulation for closely matching simulated building behavior to reality (Coakley et al., 2014). When it comes to calibration of simulation models, many approaches are available in the literature, comprising manual and iterative ones, graphical comparative procedures, techniques based on specific tests and many others (Chong et al., 2021). Among all possible approaches, the optimization-based calibration is the most widely adopted in model calibration. However, this approach, which is usually based on evolutionary algorithms, has the disadvantage that it requires many expensive simulations to be run, especially when the number of parameters to be calibrated is high, as in detailed models. This issue can be overcome by a preliminary sensitivity analysis that reduces the number of parameters to be calibrated, and by an efficient optimization algorithm.

Thus, this research work proposes a framework based on a sensitivity analysis designed to identify the most significant parameters separately on the energy budgets, other monitored environmental variables and, after that, considering all the variables together. Then, a calibration procedure is performed based on functional approximation models, which greatly increases the efficiency of the optimization algorithm. The Root Mean Square Error (RMSE) was chosen as statistical indicator to be minimized, instead of the monitored variables. The case study is a university library located in the municipality of Trento, Italy. The building is constantly monitored in terms of indoor temperature (°C), relative humidity (%) and indoor carbon dioxide (ppm). The results show how successful the proposed approach is in reducing the computational time required for calibration, especially when considering models with a high degree of complexity.

2. Methodology

2.1 Monitored Case Study

To test the proposed calibration procedure, a real building was considered, specifically, a university library placed in Mesiano (46° 3' N, 11° 8' N), municipality of Trento, Italy.

Fig. 1 – Case study: University library *BUM*, University of Trento, Trento (Italy). The building was opened in 2021. Picture retrieved from http://www.weberwinterle.com

The construction was built in 2020, and it has a total floor area of 1533 m^2. It is a three-storey building composed of an underground basement , used as an archive and technical room, and two upper floors connected by internal stairs, where rooms are mainly used as offices and lecture halls. The generation system is composed of two heat pumps, one air-to-water and a ground source one. The hydronic heating/cooling system is based on a radiant floor panel system for the two upper floors, and a fan-coil system for the basement. The building is supplied with an air mechanical ventilation system coupled with an Air Handling Unit *AHU*, except for the basement.

Sensors are installed all over the library with the aim of monitoring the indoor conditions in terms of temperature *T*, relative humidity *RH*, and levels of CO_2 in each ambient. Additional sensors are also placed on the plant side (i.e., heat pump system and the Air Handling Unit). Since its construction, the building has been constantly monitored by means of the *Schneider Building Automation Server*. Fig. 2 shows the positions of the data loggers in the library. Red sensors record indoor temperature and relative humidity, and CO_2 levels, while the green ones only record the temperature. Data were recorded with time steps of 15 min. Table 1 lists the different sensors and the names of the different zones.

Fig. 2 – Sensor locations with their identification numbers

Table 1 – Sensor list and their positioning

Sensor	Monitored quantity	Zone	Floor
1	T, RH, CO_2	Reading hall vs. Stairs	1st
2	T, RH, CO_2	Reading hall vs. Office	1st
3	T, RH, CO_2	Wardrobe	1st
4	T, RH, CO_2	Architecture hall	1st
5	T, RH, CO_2	Reading hall vs. Offices	GF
6	T, RH, CO_2	Reading hall vs. Toilets	GF
7	T, RH, CO_2	Architecture hall	GF
8	T, RH, CO_2	Conference room	GF
9	T, RH, CO_2	Archive	B
10	T	Office	1st
11	T	Meeting room	GF
12	T	Office 1	GF
13	T	Office 2	GF

2.2 Building Simulation Model

TRNSYS® (v18) software was adopted to model the building's performance.

At first, the geometry of the model was created through the TRNBUILD application in the SketchUp environment (https://www.sketchup.com/it), and then it was imported into the program through Multizone Building Modeling (*Type56*), where each thermal zone (35 in total) was defined in this subroutine, thermo-physical properties of materials adopted in the opaque components, glazing properties and so on were defined. In particular, those data were retrieved from technical datasheets of the construction company.

Weather data, in terms of external total solar radiation (W m^{-2}), external air temperature (°C), external air relative humidity (%) and wind speed (m s^{-1}), were taken from the weather station at Trento Laste (https://www.meteotrentino.it) with time steps of 1 h.

Solar radiation for each external tilted surface was modeled with the Perez Model (Perez et al., 1990) through *Type16*. The ground temperature was modeled with *Type77*. The external convective heat transfer coefficient h_{ce} was defined according to the Standard EN ISO 6946:2017 (CEN, 2017). Air infiltrations were calculated in accordance with the empirical method suggested by the ASHRAE K_1, K_2 and K_3 model (ASHRAE Handbook, 1989). Since the building is a new one, coefficients can be assumed equal to $K_1 = 0.1$, $K_2 = 0.011$ and $K_3 = 0.034$ (for tight constructions).

The light power density was taken from technical documentations and differentiated for each thermal zone. Three levels were considered, which are 20, 15 and 10 W m^{-2}, of which 60 % was accounted as thermal gain directly affecting the air node thermal balance. As regards thermal gains generated by the equipment, 7, 5 and 4 W m^{-2} power density levels were considered according to the ASHRAE Handbook (ASHRAE, 1989).

Schedules of lights, as well as of the external shading devices, were imported from an external file through *Type9*. These data come from the monitoring, since the building is also equipped with sensors giving information about the state of the lighting power in percentage terms and percentage value of the window shadings.

Since detailed occupancy schedules were not available, occupancy was assumed to follow Eq. (1).

$$occupancy_i = max\ people_i \cdot Schedule_i \qquad (1)$$

The maximum number of people for each thermal zone was obtained with the help of on-site inspection by counting the number of available chairs, while the schedule of the reading hall, a value ranging from 0 to 1, was determined by analyzing the weekly occupancy rate supplied by Google (see Fig. 3) and available because of glocalization. As regards offices, a different schedule was considered.

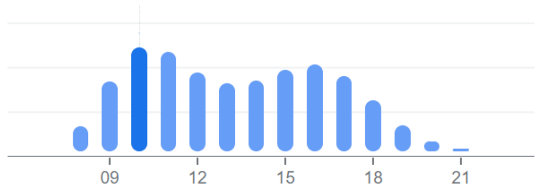

Fig. 3 – Example of occupancy rate of the library adopted as schedule for the reading hall. Profile retrieved from Google. Values range from 0 to 1. X-axis shows the time in hours

The Air Handling Unit was modeled as a black box, taking as input the monitored air temperature T_{supply} and relative humidity RH_{supply} of the supply air. In this way, composing devices were neglected. In the period monitored, the unit was working in *all-air* configuration due to COVID restrictions, thus no air recirculation was performed, and air was taken completely from the outside. Data about the supply air were passed through *Type9*. The air volume flow rate *VFR* introduced in each ventilated zone was defined as:

$$VFR=VFR_{design} \cdot Schedule_{VENT} \cdot Rg_{VENT} \quad (2)$$

where the design volume flow rate was taken from technical documentations, and the AHU schedule (expressed from 0 to 1) and the regulation of the supply ventilator expressed in percentage terms were retrieved from monitored data (through *Type9*).

The Radiant panels, adopted for both heating and cooling, were modeled through *Type1231 – Radiator* (TESS Libs 17 – HVAC Library Mathematical Reference). The general expression of the specific thermal output for a general radiator was characterized for the radiant floor system by setting a value of 1 for the exponent linked to the difference between surface temperature and air temperature. And a value of 0.2 was considered for calculating the altitude correction factor. Inlet water temperature to the radiant floor system was taken from monitored data (*Type9*) and the water mass flow rate expressed in kg hr^{-1} was defined as the product of the design water flow rate for each zone (retrieved from technical documentation) and the monitored signal relative to the functioning of the radiant floor system in that zone.

The evolution profiles of CO_2 concentrations were simulated as well. The levels of CO_2 in a room depend on the occupancy rate in that volume, the ventilation rate, and on the infiltrations. The model considered for the evolution in time of the indoor concentration accounts for the maximum value, at each time step, between the outdoor carbon dioxide $CO_{2,ext,}$ considered equal to 400 ppm, and the expression in Eq. (3).

$$\begin{aligned} CO_{2\{i,m\}} = CO_{2\{i,m-1\}} + \{ & INF \cdot (CO_{2,ext} - CO_{2\{i,m-1\}}) + \ldots \\ & \ldots + VFR_i/V_i \cdot (CO_{2,ext} - CO_{2\{i,m-1\}}) + \ldots \\ & \ldots + (k_{gen} \cdot 10^6 \cdot occupancy)/ V_i \cdot \} \cdot \Delta t \end{aligned} \quad (3)$$

The generation term is equal to 0.017568 m^3 hr^{-1} $person^{-1}$. The three terms correspond to the infiltrations, ventilation system and the occupancy, respectively.

Beyond the thermal and the occupancy balance, also the moisture one was implemented by considering the moisture production of the people according to the ASHRAE Handbook (ASHRAE, 2017), where two different levels of activity were set, both sedentary and active.

2.3 Sensitivity Analysis

To identify the most dominant parameters affecting the model's outputs, a preliminary sensitivity analysis was performed. In particular, the methodology adopted is the one proposed by Sohier et al. (2014), which is a modified version of the qualitative *Morris method*, in which the significance threshold depends on the parameter with the highest elementary factor. This modification showed improvements in the estimation of the factors' impact with respect to the original one. The sensitivity analysis was applied separately to the three balances, and in particular:

(i) at first, on the thermal balance, by considering as objective function the RMSE for the indoor temperature *T*.

(ii) second, on the humidity balance, by considering the RMSE for the indoor absolute humidity *x*.

(iii) at the end, on the CO_2 balance, by considering the RMSE for the CO_2 concentration levels.

For each case, every parameter taken into consideration was varied in a specific range, then simulations were run and the magnitude of the variation of the Root Mean Square Error RMSE, expressed in Eq. (4), was assessed.

$$RMSE_i = \sqrt{\frac{\sum_{m=1}^{N}\left(y_{i,m}^{mis} - y_{i,m}^{sim}\right)^2}{N-1}} \tag{4}$$

In particular, the *RMSE* relative to the individual variable, i.e., temperature, relative humidity, and CO_2 concentration, was calculated for each monitored zone and then averaged using the corresponding volume. The method was implemented in the MATLAB® environment, which allowed automatic link to the software TRNSYS.

2.4 Calibration Process

After the preliminary parameter screening, the calibration procedure was addressed. In particular, a meta-models-based optimization approach was adopted, which is described and discussed in detail in the work of Prada et al. (2018). Meta-models are, substantially, surrogate models that emulate building dynamics. Hence, instead of optimizing the initial building simulation code directly, an explicit expression of the code is constructed starting from the building simulation results and used together with the Genetic Algorithm *GA* for the optimization procedure. The main advantage of such meta-models is to filter out the variable domain regions with no eligible Pareto solutions, as stated by Prada et al. (2018). In particular, in this research, the surrogate model implemented is called Multivariate Adaptive Regression Splines (*MARS*) meta-model and it is based on piecewise cubic splines, which are adopted to approximate the cost function.

Such an approach aims at overcoming some issues related to the commonly adopted evolutionary algorithms, whose procedure is extremely time-consuming. The calibration was based on three monitored quantities, which are, firstly, the indoor air temperature of each zone, secondly, the absolute humidity for each ambient, except those related to sensors 10 to 13 (see Fig. 2) and, thirdly, regarding the CO_2 variable, all zones equipped with a CO_2 sensor were considered, except for the conference room and the basement (i.e., sensors 8 and 9), where the random component of the occupancy schedule was extremely significant and, thus, neglected. The objective function set for minimization is the RMSE (Eq. 4), defined separately for each monitored quantity, i.e., temperature, absolute humidity and CO_2, and normalized considering the initial case. Simulations were run considering a time-step of 15 min and a period from the 6th of November 2011 to the 12th of November 2011 (heating period). As for the sensitivity analysis, the procedure was implemented in the MATLAB® environment, which allowed an automatic link to the software TRNSYS.

3. Results and Discussion

In this section, results of the sensitivity analysis, as well as of the calibration procedure, are shown and discussed together. For instance, Table 2 shows the dominant parameters most affecting the model's output as a result of the sensitivity analysis. In particular, for each parameter, the magnitude of the influence (i.e., with numbers from 1 to 12) on each balance of temperature, of absolute humidity and of the CO_2 is specified. The term N/A is adopted when the model is not sensitive to that parameter.

The parameters most influencing the temperature variable are mainly related to material properties, i.e., specific heat capacity, infiltration rates and gains related to lights and equipment. However, gains related to occupancy and the volume flow rate of the ventilation system also have an impact on the temperature's output, as seen in Table 2. In terms of absolute humidity, the parameters affecting the balance the most are the occupancy rates and the volume flow rates of the environments where the ventilation system is installed. The same stands for the CO_2 balance, considering, in addition, the effect of the external levels of CO_2. Since parameters from no. 1 to no. 7 affect only the temperature, their calibration was performed only on the thermal balance and by considering a single objective function based on the indoor air temperature. On the other hand, the other parameters from no. 8 – 15 that have an influence either on absolute humidity, CO_2 or both, were adjusted according to a two-objective function calibration, based on such variables. In this way, the calibration procedure was decoupled. As regards parameters related to occupancy rate and volume flow rates, which influence not only the absolute humidity and CO_2, but also the temperature (e.g., no. 8, 9, 10, 12 and 13), these were accounted for in the two-objective function calibration, since they are more dominant on such balances than on the thermal one. Once parameters no. 8, 9, 10, 12 and 13 were calibrated, they were changed in the thermal balance, and the calibration of the temperature was performed. Table 2 shows the calibration ranges of each parameter, where a variation of ± 20 % from the initial value was considered.

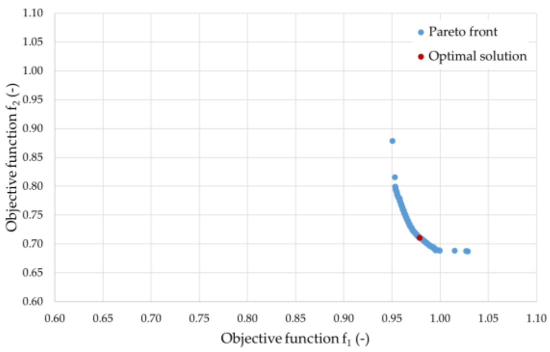

Fig. 4 – Pareto front (blue data) with the combinations of the objective functions f_1 and f_2 related to the absolute humidity AU (kg kg^{-1}) and CO_2 (ppm), respectively. The optimal solution is highlighted in red

Fig. 4 shows results of the optimization-based calibration on the absolute humidity and the CO_2, as combinations of the objective functions f_1 and f_2 expressed as the ratio between the current RMSE and the RMSE related to the initial case, both for the AU and the CO_2, respectively (see Eq. 5).

$$f_{1\ or\ 2} = \frac{RMSE_{AU\ or\ CO_2}}{RMSE_{0\,AU\ or\ CO_2}} \tag{5}$$

Results are placed on the Pareto front, as depicted in blue. By assessing the minimum distance of each solution from the origin, the optimal solution was selected and highlighted in red, as shown in Fig. 4. In particular, with this solution, only the CO_2 concentration was improved, instead of the absolute humidity, for instance, f_1 = 0.98 and f_2 = 0.71 (improvements equal to 2 % and 9 % compared with the initial case, respectively). This is because the prediction of humidity in environments was modeled with a simplified approach, which neglects some mechanisms like moisture buffering due to the building's opaque components. The values of the calibrated parameters related to this optimal solution are summarized in Table 2 from no. 8 to no. 15. Besides values of occupancy and volume flow rates of the ventilation system, the parameter which shows remarkable change with respect to the initial case is the external CO_2 concentration, which was not measured but assumed, and whose value influences the indoor CO_2 balance to a great extent, according to Eq. (3).

Results of the calibration on the thermal balance are reported in Table 2 from parameters no. 1 to 7, which refer to the minimum value of the objective function as expressed in Eq. 5, but only in terms of temperature. The obtained temperature objective function was equal to 0.90, which means a 10 % improvement compared with the initial case. In particular, parameters related to air infiltrations slightly decrease from the initial values, confirming the hypothesis of a highly airtight building, typical of new constructions.

Table 3 shows the computational effort of each calibration procedure (in h), the percentage improvement of the model with respect to the initial case expressed as 1- *f* and the calibration accuracy in terms of RMSE for each variable. In particular, three cases were reported: the initial one, the case after the decoupled calibration composed of *Cal 1* and *Cal 2*, which considered the joined AU and CO_2, and T, respectively. And, at the end, a third case based on a standard calibration procedure (*Cal 3*) taken only as a comparison. Specifically, the calibration considered all parameters of Table 2 and three objective functions for every variable implemented together. The computational time necessary for the decoupled calibration is about 32 h considering both Cal_1 and Cal_2. Clearly, Cal_1 is remarkably more time-consuming than Cal_2 (i.e., 30.8 h vs 1.2 h) because of the two objective functions. The improvement obtained after the decoupled procedure with respect to the initial case is 2 % for the absolute humidity, 29 % for the CO_2 and 10 % for the temperature. In terms of RMSE, it can be noticed that the variations with the initial case are limited especially in terms of temperature and absolute humidity prediction. A more marked reduction in the RMSE(CO_2) is evident, i.e., from 88.3 ppm to 61.6 ppm. This is because the model was already robust at the beginning thanks to the reliability of the input data and parameters - a typical condition of new constructions. As regards the standard case, results in Table 3 show that the calibration procedure requires about 9 % more time than the decoupled case (i.e., 35 h vs 32 h) to get a comparable accuracy, or even slightly lower, when considering the CO_2 prediction. As before, the improvement is not greatly higher than the initial case because of the goodness of the initial model.

Table 2 – Parameters which influence the most the models' output obtained from the sensitivity analysis

Category	No.	Parameter	T	AU	CO2	Values range	Calibrated value
Material properties	1	*c* reinforced concrete [kJ kg^{-1} K^{-1}]	3rd	N/A	N/A	[0.704-1.056]	1.03
	2	*c* concrete - heated floor [kJ kg^{-1} K^{-1}]	11th	N/A	N/A	[0.704-1.056]	0.95
Infiltration rate	3	*K1* – INF [-]	5th	N/A	N/A	[0.08-0.12]	0.08
	4	*K2* – INF [-]	2nd	N/A	N/A	[0.088-0.0132]	0.009
Gains from lights and equipment	5	Light power density -1st level [kJ hr^{-1} m^{-2}]	1st	N/A	N/A	[58-86]	59
	6	Light power density – 2nd level [kJ hr^{-1} m^{-2}]	9th	N/A	N/A	[43-65]	63
	7	Equipment power density – 1st level [kJ hr^{-1} m^{-2}]	8th	N/A	N/A	[20-30]	20
Gains from people	8	Max *PPL* Reading hall vs. Stairs 1st [-]	4th	2nd	2nd	[50-74]	70
	9	Max *PPL* Reading hall vs. Offices 1st [-]	6th	1st	N/A	[6-10]	6
	10	Max *PPL* Reading hall vs. Offices GF [-]	12th	4th	N/A	[26-30]	26
	11	Max *PPL* Reading hall vs. Toilet GF [-]	N/A	N/A	3rd	[32-48]	32
Ventilation	12	*VFR* Reading hall vs. Stairs 1st [m3 hr^{-1}]	7th	3rd	N/A	[888-1332]	1024
	13	*VFR* Reading hall vs. Offices GF [m3 hr^{-1}]	10th	5th	5th	[435-653]	645
	14	*VFR* Reading hall vs. Toilet GF [m3 hr^{-1}]	N/A	N/A	4th	[544-816]	773
External environmental conditions	15	$CO_{2,\,ext}$ [ppm]	N/A	N/A	1st	[200-600]	514

Table 3 – Computational time, improvement and accuracy of the decoupled and standard calibration approach

	Initial case	Decoupled			Standard
		Cal 1		*Cal 2*	*Cal 3*
Calibration Time*	-	30.8 h		1.2 h	35 h
Improvement 1-*f*	-	2 % (AU)	29 % (CO_2)	10 % (T)	5 % (AU) 28 % (CO_2) 7 % (T)
RMSE$_T$ **RMSE$_{AU}$** **RMSE$_{CO2}$**	0.6 °C 0.3 g kg^{-1} 88.3 ppm	0.6 °C 0.3 g kg^{-1} 61.6 ppm			0.6 °C 0.3 g kg^{-1} 63.6 ppm

* Processor: AMD Ryzen 9 5950X 16-Core – 3.40 GHz; Installed RAM: 32.0 GB.

4. Conclusions

In this work, a calibration of an energy simulation model based on the meta-model optimization approach was tested on a real case study. The methodology comprised a first sensitivity analysis designed to identify the most significant parameters on the energy budgets and other monitored environmental variables separately. Then, a calibration procedure based on functional approximation models was applied separately on the monitored variables, which are temperature, humidity and CO_2. The case study is a university library placed in the municipality of Trento, Italy. The building was monitored in terms of indoor carbon dioxide, indoor temperature, and relative humidity. Results show how the decoupled approach increases the efficiency of the optimization algorithm, especially in energy simulation codes with a high degree of complexity, thus with a high number of parameters. For instance, to obtain the same, or even slightly greater, accuracy than a standard calibration approach, the computational time required for this decoupled calibration is 9 % less than a standard approach, where no differentiation among monitored variables is performed. Hence, the adoption of the *MARS* model in calibration procedures of building simulation models can provide a contribution towards the optimization of both building refurbishment design, as well as building operation and control.

Nomenclature

Symbols

ACH	Air Changes per Hour (h^{-1})
AHU	Air Handing Unit
B	Basement
c	Specific heat capacity (kJ kg^{-1} K^{-1})
CO_2	Carbon Dioxide (ppm)
Δt	Simulation time step (hr)
GA	Genetic Algorithm
GF	Ground Floor
H/C	Heating/Cooling
h_{ce}	External convective heat transfer coefficient (kJ hr^{-1} m^{-2} K^{-1})
INF	Infiltration rate (h^{-1})
λ	Thermal conductivity (W m^{-1} K^{-1})
N	Number of simulation time steps
k_{gen}	Generation rate (m3 hr^{-1} $person^{-1}$)
PPL	People
Rg	Regulation
RH	Relative Humidity (%)
RMSE	Root Mean Square Error
T	Indoor air temperature (°C)
X	Absolute humidity (kg kg^{-1})
Y	Variable (either T, RH or CO_2)
VFR	Volume Flow Rate (m^3 hr^{-1})

Subscripts/Superscripts

ext	External
i	Of the i^{th} thermal zone
mis	Measured
m	Of the current time step (-)
m-1	Of the previous time step (-)
sim	Simulated
supply	Of the supply air of the AHU
VENT	Of the supply ventilator

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