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Impact of interactions between buildings and their outdoor conditions on the calibration of an urban building energy model

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Abstract

Urban Building Energy Models (UBEMs) often ignore interactions between buildings and their outdoor conditions. To determine their importance when calibrating an UBEM, this study performed various statistical analyses using a coupling between detailed building energy models and a data driven urban canopy model. Results of statistical analyses suggest that the sensitivity of an UBEM with respect to uncertain parameters is affected by interactions between buildings and their outdoor conditions. They also reduce the probability to reach requirements for calibration. The reason is that interactions between buildings and their outdoor conditions are an important factor driving the goodness-of-fit of an UBEM.

Introduction

Since the 19th century, a significant portion of the world population has been migrating from rural to urban areas. This migration has caused a considerable expansion of the built environment to accommodate inhabitants. The expansion of the built environment has consequences on both the amount of energy consumed in buildings and the livability of the outdoor space in cities. According to Cao et al. (2016), more than 40% of the total energy consumed in Europe and United States originates from buildings. When energy is consumed to cool the indoor of a building using an air-conditioning system, heat is released into the outdoor environment. Heat releases resulting from air-conditioning, together with the heat stored by the envelope of buildings over the day, are responsible for the exacerbation of urban heat islands. This climatic phenomenon becomes a major issue to the development of sustainable cities in Europe and United States as the demand for indoor space cooling is expected to increase due to global warming (Larsen et al., 2020; Wang & Chen, 2014).

To prevent shortages of energy supply and degradations of outdoor conditions in cities for the years to come, it is thus crucial to have an assiduous control on the energy consumed in buildings. A review published by Ahmad et al. (2016) shows various solutions that have been used to measure and observe the energy consumption in buildings, as well as their outdoor environment. However, measurements are provided over a limited number of buildings and spots in the outdoor environment. They also give information about the past and present status of the energy consumed by buildings and their outdoor environment, but they cannot be directly used to make predictions in the years to come.

The spatial resolution and time horizon of observations made on the energy consumed in buildings can be enhanced using an UBEM. Reinhart and Cerezo Davila (2016) define an UBEM as a set of physically-based Building Energy Models (BEMs) from which it is possible to assess both the energy consumed by a group of buildings and their outdoor conditions. Although the assessment of outdoor conditions in an urban neighbourhood was an original consideration in UBEMs, most of them solely predict the building energy demand as illustrated in several reviews (Ali et al., 2021; Ang et al., 2020; Dahlström et al., 2022; Ferrando et al., 2020). A reason mentioned by Johari et al. (2020) is that outdoor conditions at the neighbourhood scale have essentially been assessed using Computational Fluid Dynamic (CFD) models, with which outdoor air flow and temperature can be estimated with a high spatial resolution. This method requires considerable computational efforts, and thus, can hardly be coupled with a set of physically-based BEMs to predict the energy use and outdoor conditions in an urban neighbourhood with a high temporal resolution and over a large time horizon.

By ignoring the impact of buildings on outdoor conditions, and vice versa, most UBEMs assess the energy use at the neighbourhood scale considering buildings as isolated elements whose outdoor conditions are equivalent to the ones recorded by a rural weather station. This assumption has consequences on the way UBEMs are automatically calibrated against measurements of the building energy use. Whether a deterministic (Chen et al., 2019; Herbinger et al., 2023) or stochastic (Cant & Evins, 2022; Chong et al., 2017) approach is used to automatically calibrate uncertain parameters of an UBEM, building energy simulations are performed as standalone processes without any interaction with a model that predict outdoor conditions at the neighbourhood scale.

Given the absence in considering interactions between buildings and their outdoor conditions at the neighbourhood scale in most UBEMs, in particular during their automatic calibration, the paper aims at providing a response to the following research question: how significantly interactions between buildings and their outdoor conditions affect the calibration of an UBEM?

A response to the research question would enable the scientific community and practitioners to better understand the necessity to consider interactions between buildings and outdoor conditions in the development of an UBEM as stated by Ang et al. (2020). In this study, it is explained that the calibration of an UBEM is a crucial step before testing new neighbourhood designs, climate change mitigation strategies, building-level retrofitting solutions, and building-to-grid integration methods. It is therefore of high importance to determine if the reliability of a calibrated UBEM could potentially be affected by neglecting interactions between buildings and outdoor conditions over its development.

Methods

To answer the question, interactions between buildings and outdoor conditions were simulated using detailed BEMs coupled with a data driven Urban Canopy Model (UCM). In contrast with urban microclimate models relying on computational fluid dynamics, the data driven model is able to estimate outdoor air temperature and humidity with a high temporal resolution and over a long period. Using the coupled scheme, various statistical analyses were conducted to show the impact of interactions between buildings and their outdoor conditions on the assessment of uncertain parameters of an UBEM. First, it was observed how the sensitivity of detailed BEMs towards uncertain parameters can be affected whether interactions between buildings and their outdoor conditions are considered or not during simulations. Sensitivity analysis is a major step during the calibration of an UBEM to select the uncertain parameters with major impacts on the goodness-of-fit between estimates of the energy consumed by buildings and measurements. Then, the distribution of the goodness-of-fit was assessed from estimates of the building energy consumption resulting from coupled and uncoupled simulations. The objective was to show the probability of the goodness-of-fit to be lower than a threshold of tolerance knowing values of uncertain parameters. Finally, a linear regression analysis was performed to determine the statistical significance of interactions between buildings and their outdoor conditions on variations of the goodness-of-fit while calibrating an UBEM. The analysis also provides the significance of uncertain parameters on variations of the goodness-of-fit independently from the fact that interactions between buildings and their outdoor conditions are considered or not during simulations.

Coupled scheme

Figure 1 describes how interactions between buildings and their outdoor conditions are simulated using detailed BEMs that are coupled with a data driven UCM. Boundary conditions of BEMs are defined by weather files, which contains data collected by a rural weather station by default. To consider weather conditions in their urban context, data stored in weather files were iteratively adjusted by a data driven UCM, whose mathematical definition and validation is explained in Martin et al. (2024). The data driven UCM provides as outputs the outdoor air temperature and humidity in a street canyon and takes as inputs the surface temperature of surrounding building facades and waste heat releases caused by the use of air conditioning. Waste heat releases are assessed from the cooling load estimated by the sequence of detailed BEMs.

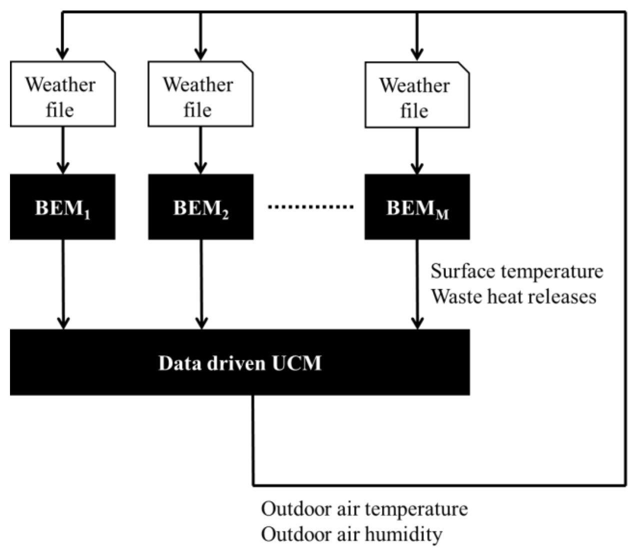

Figure 1. Coupling between detailed building energy models and a data driven urban canopy model.

Information between detailed BEMs and the data driven UCM are exchanged through a one-time-step dynamic coupling as stated by Zhang et al. (2018). It means that information are iteratively exchange over the whole period of simulation until a convergence criterion or steady state condition is achieved. In the coupled scheme between detailed BEMs and the data driven UCM, convergence or steady state is assumed to be achieved if the difference between the mean cooling load among all buildings obtained at two subsequent iterations falls below a threshold of tolerance. The tolerance can be expressed either as an absolute or relative value depending on the metric it is used to express the discrepancy in the cooling load.

As any data driven model, the UCM consists of parameters that need to be assess using measurements. Measurements are the outdoor air temperature and humidity collected by several weather stations with a street canyon. Because the data driven UCM considers the street canyon as an air volume of uniform temperature and humidity, the means collected by all weather stations are used to train the model. At least, the data driven UCM needs to be trained at each iteration of coupled simulations until achieving steady state conditions once. Trained parameters can then be reused for further simulations using the coupled scheme.

Using the trained data driven UCM, and its coupling with detailed BEMs, interactions between buildings and their outdoor conditions can be simulated while considering urban morphology with a high level of details. It can also provide estimates of the cooling load and outdoor conditions with a high temporal resolution and over a long period due to the rapidity with which simulations can be performed with the data driven UCM.

Sensitivity analysis

Given a set of detailed BEMs being coupled or not with the data driven UCM, the sensitivity of their goodness-of-fit (F) towards uncertain parameters ($\boldsymbol{\theta}$) was assess using the method defined by Morris (1991). This method primarily consists of evaluating the distribution f_i of the effect of θ_i on variations of F from randomly generated samples of $\boldsymbol{\theta}$. The sensitivity of F towards various θ_i can thus be analysed from the mean μ_i and standard deviation σ_i of their respective f_i. To generated reliable values of μ_i and σ_i using the Morris method, it is usually recommended the sampling size to be at least $10 * (K + 1)$, where K is the number of parameters $\boldsymbol{\theta} = [\theta_1, \theta_2, \dots, \theta_K]^T$. Among various possible formulations of F, the Coefficient of Variation of the Root Mean Square Error (CVRMSE) was used, that is:

$$F = \frac{100}{\bar{P}} \sqrt{\frac{1}{N} \sum_{n=0}^{N} \left(P_n - \hat{P}_n\right)^2} \qquad (1)$$

where P_n is the cooling load (in W) of a building to be fitted during calibration at time $t_n = t_0 + n \cdot \Delta t$, $\hat{P}_n$ its estimate given by a detailed BEM being coupled or not with the data driven UCM, $\bar{P}$ its average, and N the total number of time steps over the period of analysis. This expression of F is commonly used in most calibration procedures of BEMs and recommended by various standards or guidelines like ASHRAE, IPMP, or FEMP (Hou et al., 2021).

Distribution analysis

According to standards or guidelines for calibration, a BEM is considered to be calibrated under certain values of $\boldsymbol{\theta}$ if F is lower than 20% or 30%. To evaluate whether interactions between buildings and their outdoor conditions affect the probability of F to be lower than these thresholds knowing $\boldsymbol{\theta}$, samples generated during the sensitivity analysis were used to estimate the probability density function $f(F|\boldsymbol{\theta})$ when F is assessed from coupled and uncoupled simulations. The probability of F to be lower than a threshold z knowing $\boldsymbol{\theta}$ can thus be expressed as:

$$\Pr[F \leq z|\boldsymbol{\theta}] = \int_{-\infty}^{z} f(F|\boldsymbol{\theta})\, dF \qquad (2)$$

As F varies between 0 and $+\infty$, a gamma function $\Gamma(k, \theta)$ was considered to estimate $f(F|\boldsymbol{\theta})$ from samples F with respect to various values of $\boldsymbol{\theta}$ that were generated from coupled and uncoupled simulations. Parameters of the gamma function were computed using a curve fitting of an histogram generated from samples of F.

Linear regression analysis

The importance of considering interactions between buildings and their outdoor conditions during the calibration of an UBEM was finally evaluated from the following linear regression model:

$$F = \beta + \sum_{k=1}^{K} \alpha_k \cdot \theta_k + \alpha_{K+1} \cdot C \qquad (3)$$

where C is a dummy variable equal to 1 if F was assessed from coupled simulations and 0 otherwise. The t-statistic and the P-value corresponding to each coefficient α_k was used to determine the statistical significance of θ_k and C to variations of F.

Studied area

The impact of interactions between buildings and their outdoor conditions on the calibration of an UBEM was studied using measurements and information collected in Singapore. Due to its tropical climate, Singapore is an ideal location to evaluate the importance of interactions between buildings and their outdoor conditions. On the one hand, the energy consumed in buildings in Singapore is largely due to air conditioning. According to Chua et al. (2013), air conditioning is responsible for about 60% of the total electricity consumed in buildings in Singapore. On the other hand, because of its high concentration of buildings, Singapore experiences urban heat islands of high magnitude. Wong and Yu (2005) observed that temperature differences at night can reach up to 3 K between suburban and highly dense urban areas in Singapore.

Although air conditioning and urban heat islands have been a more pressing issue in Singapore in comparison to North parts of Europe and United States, for instance, the situation at these locations are expected to change in the future if climate change persists. Consequently, any observation made in Singapore with respect to building energy consumption and urban outdoor environment can be used to prevent potential hazards in other parts of the world.

Figure 2 shows the area that was considered to study interactions between buildings and their outdoor conditions using the coupled scheme. Whether interactions between buildings and their outdoor conditions are considered or not during simulations, the UBEM consist of detailed BEMs of buildings A, B, and C. These buildings are separated by asphalt road of width about 10 meters. Their function is to accommodate researchers of an university campus to work or conduct experiments. Air-conditioning in the buildings is supplied by a district system whose central chiller plant is installed at the rooftop of a building located at about 200 meters from the studied area. Little traffic is observed on the road between buildings A, B, and C. Therefore, the outdoor air temperature at this location is primarily affected by the surface temperature of walls, windows, and the road.

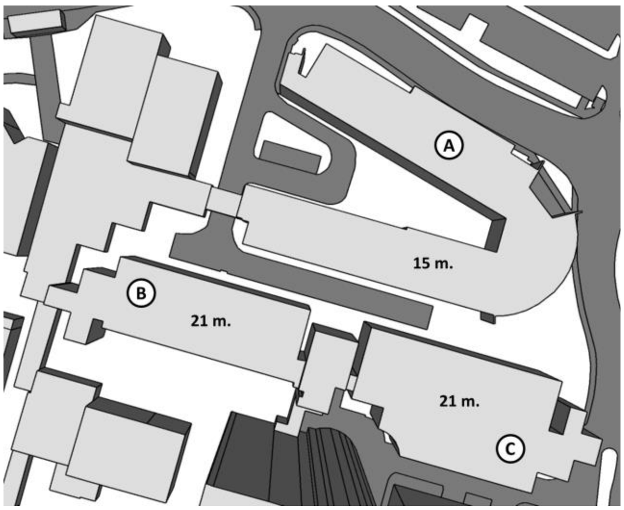

Figure 2. Studied area to evaluate the impact of interactions between buildings and their outdoor environment on the calibration of an UBEM.

Simulation and calibration setup

To estimate the energy consumed in buildings A, B, and C, EnergyPlus simulations were performed between June 9 and August 20 2024 with a 10-minute timestep. An original configuration containing material properties, internal heat gains, and the air-conditioning system of buildings was created to generate the cooling load to be fitted by the UBEM. In practice, metered data of the building energy consumption should be used to calibrate the UBEM instead of simulated ones. However, the aim of this study is not to prove the accuracy of a calibration method, but instead, showing divergences in using coupled and uncoupled simulations to find $\boldsymbol{\theta}$ of an original state of the UBEM.

Simulations of interactions between buildings A, B, and C their outdoor conditions was thus performed by coupling their respective EnergyPlus model to a data driven UCM. The data driven UCM was trained using measurements of weather conditions at the studied area. The measurements were collected by Miguel et al. (2021) between April and August 2019, and essentially consist of the outdoor air temperature (T_{out}), the outdoor air humidity (q_{out}), and the road surface temperature. Atmospheric conditions were assumed to be equal to typical meteorological conditions recorded by a rural station in Singapore. Over a total of 10368 samples of T_{out} and q_{out}, the data driven UCM was trained on 80% of them, which is a ratio where a root mean square error of 2.16 K and 3.82 g/kg can be obtained between estimates and measurements of the outdoor air temperature and humidity, respectively. The convergence of co-simulations between buildings A, B, and C, and their outdoor conditions was established based on the CVRMSE of sensible and latent loads estimated at each iteration. If the CVRMSE falls below 0.1% for sensible loads and 0.2% for latent loads, steady state between detailed BEMs and the data driven UCM is assumed to be achieved.

A total of twelve parameters were considered as uncertain parameters ($\boldsymbol{\theta}$) of the UBEM as shown in Table 1. Using the Morris sampler, more than 800 samples of $\boldsymbol{\theta}$ were generated within their range of uncertainty. For each sample of $\boldsymbol{\theta}$, the corresponding F was computed from coupled and uncoupled simulations to perform sensitivity, distribution, and linear regression analyses.

Table 1. Description of uncertain parameters ($\boldsymbol{\theta}$) of the UBEM, including their lower ($\boldsymbol{\theta}_l$) and upper ($\boldsymbol{\theta}_u$) bounds.

$\boldsymbol{\theta}$	**Description**	$\boldsymbol{\theta}_l$	$\boldsymbol{\theta}_u$
θ_1	Occupancy (in people)	1.21×10^2	3.03×10^3
θ_2	Light intensity (in W)	1.21×10^4	1.21×10^5
θ_3	Equipment intensity (in W)	1.82×10^4	1.82×10^5
θ_4	Infiltration (in m^3/s)	0.01	10.00
θ_5	Wall thermal resistance (in W/m^2-K)	0.05	3.00
θ_6	Wall density (in kg/m^3)	3.00×10^2	1.80×10^3
θ_7	Wall specific heat capacity (in J/kg-K)	4.00×10^2	1.50×10^3
θ_8	Wall thermal emissivity (0-1)	0.01	0.98
θ_9	Wall solar absorptivity (0-1)	0.05	0.90
θ_{10}	Window-to-wall ratio (0-1)	0.01	0.90
θ_{11}	Window thermal resistance (in W/m^2-K)	0.04	1.50
θ_{12}	Window solar heat gain (0-1)	0.20	0.90

Results and discussion

Impact of the coupled scheme on the sensitivity analysis

Figure 3 and Table 1 shows the impact of the twelve parameters on the CVRMSE achieved by the cooling load estimated by BEMs of buildings A, B, and C. Some parameters appears to have an increased impact on variations of the CVRMSE if simulations are performed using coupled BEMs instead of uncoupled ones. It comprises parameters having an influence on the penetration of outdoor air into the indoor of a building like infiltration. It also includes parameters that strongly affect the surface temperature walls like their thermal resistance and solar absorptivity. The impact of other parameters on variations of the CVRMSE does not seem to be considerably affected by coupled versus uncoupled simulations. Regarding parameters related to internal heat gains like occupancy, light intensity, and equipment intensity, it can be explained from the fact that waste heat releases, and thus building cooling consumption, has no impact on outdoor conditions of the case being considered for this study. In cases where waste heat releases affect outdoor conditions, it is possible that internal heat gains have a different impact on variations of the CVRMSE whether simulations are performed using coupled or uncoupled BEMs.

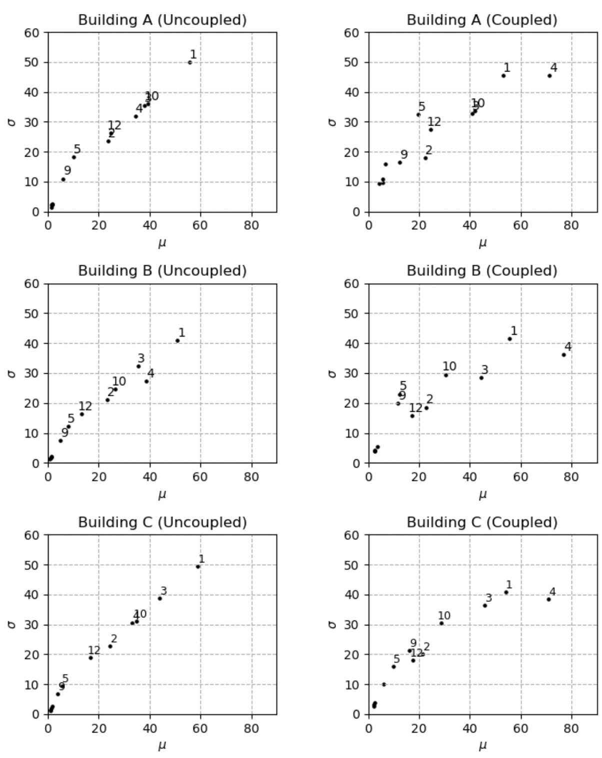

Figure 3. Sensitivity of BEMs for buildings A, B, and C against twelve parameters when CVRMSE is assessed from uncoupled and coupled simulations.

Table 2. μ-values predicted by the Morris method associated to twelve parameters of BEMs developed for building A, B, and C when being uncoupled (U) or coupled (C) with the data driven UCM.

θ	Building A		Building B		Building C	
	μ(U)	**μ(C)**	**μ(U)**	**μ(C)**	**μ(U)**	**μ(C)**
θ_1	55.6	53.0	51.0	55.6	58.9	54.0
θ_2	23.7	22.4	23.5	22.8	24.3	21.4
θ_3	37.9	40.8	35.4	44.4	43.9	45.6
θ_4	**34.5**	**71.2**	**38.8**	**76.9**	**33.1**	**71.0**
θ_5	**10.3**	**19.8**	**7.9**	**12.4**	**5.6**	**9.8**
θ_6	1.8	5.6	1.4	2.7	1.0	2.5
θ_7	1.4	4.1	1.2	3.7	1.0	2.2
θ_8	1.6	5.7	1.4	2.5	1.6	6.1
θ_9	**6.0**	**12.3**	**5.0**	**11.8**	**3.9**	**16.0**
θ_{10}	39.5	41.8	26.4	30.4	35.0	28.6
θ_{11}	1.4	6.6	0.8	2.5	1.3	2.3
θ_{12}	24.6	24.3	13.3	17.3	16.9	17.5

Impact of the coupled scheme on the distribution of the goodness of fit

Figure 4 illustrates the probability density function of the CVRMSE knowing values of the twelve uncertain parameters. The probability density function assessed from uncoupled simulations looks different from the one evaluated from coupled simulations. While the shape of the gamma function is relatively similar in both cases, the most visible difference is observed on the scale parameter. It then implies that the CVRMSE varies more when the cooling load is estimated using the coupled scheme within the range of uncertain parameters than when assessed using uncoupled BEMs. A consequence is that a calibration method relying on coupled simulations, in particular a deterministic method, will take more time to find a set of parameters that meets requirements stated by ASHRAE, IPMP, or FEMP standards for calibration.

Table 3 shows the probability a calibration method has to find a set of parameters that meets these requirements when simulations are performed using uncoupled and coupled BEMs. In some cases, like in building A, this probability can be reduced by half if the cooling load is estimated from coupled simulations instead of uncoupled ones. It means that methods to calibrate a coupled scheme need to be more effective in the exploration of parameters that can potentially provide a good agreement against the target cooling load. It also suggests that surrogate models and posterior distributions can be more difficult to train and assess, respectively, when a stochastic method of calibration uses coupled simulations to estimate the energy use in buildings.

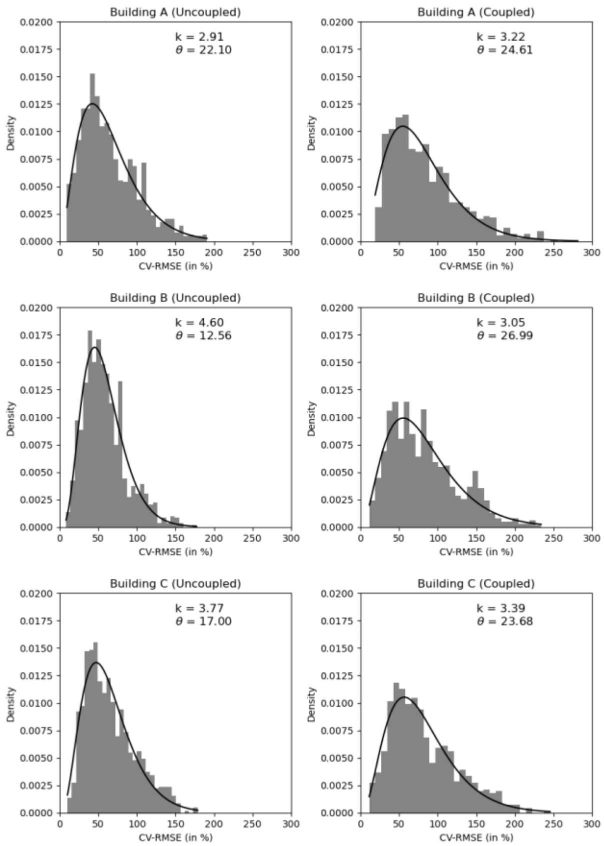

Figure 4. Probability density function of the CVRMSE achieved by estimates of the cooling load in buildings A,B, and C over several values of uncertain parameters when their respective BEMs are uncoupled or coupled.

Table 3. Probability (in %) that the CVRMSE achieved by estimates of the cooling load in buildings A, B, and C is lower than 20% and 30% when BEMs are uncoupled and coupled with the data driven UCM.

	Building A		**Building B**		**Building C**	
	20%	30%	20%	30%	20%	30%
Uncoupled	7.2	17.2	3.9	13.5	4.4	13.0
Coupled	3.5	9.6	3.7	9.6	3.0	8.6

Significance of the coupled scheme to variations of the goodness of fit

Table 4 describes the statistical significance of uncertain parameters to variations of the CVRMSE. It also shows the significance of performing simulations using either uncoupled or coupled BEMs. Based on observation made during the sensitivity analysis, results suggest that parameters like the wall density, specific heat, and emissivity have no significance on variations of the CVRMSE whether the cooling load is estimated from uncoupled or coupled simulations. The low significance of wall density and specific heat can be explained from the method used by EnergyPlus to evaluate the outer surface temperature. EnergyPlus uses a steady state heat balance, and thus, neglect the heat stored by the outer surface of the wall. The wall emissivity could also have a more significant importance on variations of the CVRMSE if longwave emissions from walls were more properly considered by EnergyPlus as pointed out by Miguel et al. (2021).

Whether simulations are performed using uncoupled or coupled BEMs, infiltration seems to be the most significant parameter to variations of the CVRMSE. It is certainly due to the fact that infiltration is the parameter that determines the most the influence of outdoor conditions in the indoor of buildings. During the sensitivity analysis, it was observed that the impact of infiltration on variations of the CVRMSE is considerably magnified when simulations are performed using the coupled scheme.

The wall solar absorptivity, which was an important parameter observed during the sensitivity analysis, appears to have a different significance depending on the building it is considered. When the façade connected to the street canyon is primarily covered by shadow during the period of simulations, like building A, the significance of the wall solar absorptivity looks negligible. It becomes more significant on buildings like B and C whose facades are highly exposed to the sun.

In comparison to all uncertain parameters that have an influence on the variations the CVRMSE, the consideration of uncoupled or coupled simulations itself appears to have a high statistical significance. It means that interactions between buildings and their outdoor environments do considerably affect the automatic calibration of an UBEM.

*Table 4. t-statistic (t) and P-value test with 5% threshold (P<5%) of uncertain parameters (**$\boldsymbol{\theta}$**) and interactions between buildings and their outdoor conditions (C) to variations of the CVRMSE.*

$\boldsymbol{\theta}$	**Building A**		**Building B**		**Building C**	
	t	***P*<5%**	***t***	***P*<5%**	***t***	***P*<5%**
θ_1	27.1	Yes	35.4	Yes	28.8	Yes
θ_2	10.0	Yes	11.1	Yes	8.9	Yes
θ_3	14.7	Yes	21.3	Yes	18.4	Yes
θ_4	27.0	Yes	37.6	Yes	29.8	Yes
θ_5	-3.4	Yes	-2.9	Yes	0.1	No
θ_6	-1.1	No	-0.7	No	-0.6	No
θ_7	-3.6	Yes	-1.7	No	-0.8	No
θ_8	-2.8	Yes	-1.7	No	-0.6	No
θ_9	2.0	Yes	7.8	Yes	8.0	Yes
θ_{10}	24.5	Yes	20.1	Yes	16.3	Yes
θ_{11}	2.7	Yes	-2.9	Yes	3.7	Yes
θ_{12}	15.7	Yes	12.6	Yes	10.2	Yes
C	17.4	Yes	21.8	Yes	16.3	Yes

Conclusion

The paper showed the impact that interactions between buildings and outdoor conditions have on the calibration of an UBEM. The UBEM consisted of detailed BEMs that are either uncoupled or coupled with a data driven UCM. Detailed BEMs were made and the data driven UCM was trained using data collected in an university campus of Singapore. From uncoupled and coupled BEMs, it was first studied the sensitivity of the goodness-of-fit with respect to twelve uncertain parameters that could be considered for calibration of the UBEM. By goodness-of-fit, it is here referred as the disagreement between estimates of the cooling load provided by uncoupled or coupled BEMs and the one generated from an original setup of the UBEM. After the sensitivity analysis, the distribution of the goodness-of-fit achieved by uncoupled and coupled BEMs was analysed to determine the probability to find values of uncertain parameters that meets requirements stated by standards or guidelines for calibration. Finally, a linear regression analysis was performed to evaluate the statistical significance of uncoupled and coupled simulations on variations of the goodness-of-fit.

The sensitivity analysis reveals that some uncertain parameters to be calibrated can have a different impact on variations of the goodness-of-fit whether simulations are performed using uncoupled or coupled BEMs. It is particularly true for a parameter like infiltration which highly influence the immediate impact of outdoor conditions on the indoor of buildings. On the other hand, parameters like occupancy, lighting, and electric equipment could also have an increased impact on variations of the goodness-of-fit if waste heat releases were considered by coupled simulations. For this reason, it would be worth applying the same sensitivity analysis on a case study that consists of buildings with rooftop chiller plants.

The distributions of the goodness-of-fit assessed from uncoupled and coupled simulations shows that interactions between buildings and their outdoor conditions affect the probability to find values for uncertain parameters that meets expectation of most standards and guidelines for calibration. This outcome suggests that methods to calibrate coupled simulations should make a more effective and fast exploration of the various possible values for uncertain parameters. For this reason, coupled simulations that rely on CFD to assess outdoor conditions can hardly be used for calibration of an UBEM. Instead, UBEMs should consists of partially or fully data driven based models to be calibrated while considering interactions between buildings and their outdoor environment.

The linear regression analysis provides a final response of the research question of this study by showing the statistical significance of coupled simulations on variations of the goodness-of-fit. It implies that most UBEMs presented in the literature should have not neglect the importance of interactions between buildings and their outdoor conditions while performing simulations using an UBEM, and in particular during its calibration. However, it is important to mention that this conclusion was reached on a single case study, and should then be checked in different climates, urban areas, and building functions at least.

Apart from these observations, it is important to highlight that statistical analyses were performed using a coupled scheme that does not take into account the wind environment with a high fidelity. The wind environment is indeed a significant parameter to consider when simulating interactions between buildings and their outdoor environment. It should thus be included in future improvements of the coupled scheme.

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