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TOWARDS A FULL DATA DRIVEN COUPLED SCHEME TO SIMULATE INTERACTIONS BETWEEN BUILDINGS AND THEIR OUTDOOR CONDITIONS AT THE CITY-SCALE

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ABSTRACT
This paper suggests a method to simulate interactions between buildings and their outdoor conditions at the city-scale using a coupled scheme whose physical parameters are entirely assessed from data of the indoor and outdoor built environment. The coupled scheme consists of a reduced order building energy model and a single layer urban canopy model. In a previous study, it was proven that physical parameters of a single layer urban canopy model can be assessed using measurements of the outdoor temperature and humidity in a street canyon. For the coupled scheme to be fully data driven, the next step is to demonstrate that the reduced order building energy model can estimate the cooling consumption and exterior wall surface temperature in good agreement with measurements or simulated data after being trained using machine learning. Indeed, results show that a multi objective genetic algorithm can find values for physical parameters of the reduced order building energy model. Estimates of the cooling consumption and exterior wall surface temperature provided by the trained model achieve a CV-RMSE below 10% and a RMSE lower than 2.5 Kelvin, respectively, with respect to data generated from EnergyPlus. The last step towards a full data driven coupled scheme for city-scale simulations would be to iteratively train the reduce order building energy model with the single layer urban canopy model and show the convergence and accuracy of their respective outputs.

KEYWORDS
Building energy modelling, Machine learning, 3D city modelling, Weather data collection, and Climate risk assessment.

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INTRODUCTION

Cities are the main contributors of climate change. It has been reported that they are responsible for more than 80% of total greenhouse gas emissions in the world (Hoornweg et al., 2020). This amount originates from the energy consumed by buildings and the combustion of fuel by cars. The building energy consumption, in particular, is affected by climatic hazards like urban heat islands. Inversely, urban heat islands are magnified because of the heat absorbed by building materials and released by air-conditioning systems. It is therefore crucial to understand how buildings interact with their outdoor conditions in a city to predict its impact on climate change.

A review published by Ali et al. (2021) shows that models used to assess the energy consumed by buildings at the neighborhood- or city-scale ignore interactions with their outdoor conditions. As explained in Sezer et al. (2023), the reason is that interactions between buildings and their outdoor conditions are commonly simulated using a detailed Building Energy Model (BEM) like EnergyPlus which is coupled with an Urban Microclimate Model (UMM) relying on Computational Fluid Dynamics (CFD). Such a coupled scheme can yet be used to simulate interactions between buildings and their outdoor conditions at the building scale, but not at higher scales.

To simulate interactions between buildings and their outdoor conditions at higher scales, Martin et al. (2024) made a first step by coupling detailed BEMs with a data driven single layer Urban Canopy Model (UCM). Using a data driven UCM, it was possible to consider urban morphology with the same level of detail as in CFD-based simulations, while estimating outdoor conditions with a higher temporal resolution. Despite that, Martin et al. (2017) mentioned that a detailed BEM requires at least four times more computational efforts than a reduced order one, that is a BEM whose number of variables and equations has been reduced.

Consequently, it seems that a viable strategy to simulate interactions between buildings and their outdoor conditions at the city-scale is to couple reduced order BEMs with a single layer UCM as in Martin et al. (2024). At this scale, it is difficult to imagine that physical parameters of reduced order BEMs would be assigned manually. It implies that reduced order BEMs should be data driven like the UCM to perform city-scale simulations. With this regard, Rouchier et al. (2018) shows that physical parameters of a reduced order BEM can be assessed using a data driven approach. However, reduced order BEMs considered in this study do not consider the exterior wall surface temperature, which is fundamental parameter to couple the model with any UCM.

For this reason, as a second step towards a full data driven coupled scheme to perform simulation of interactions between buildings and their outdoor conditions at the city-scale, this paper aims at defining a reduced order BEM that can be coupled with a single layer UCM and whose physical parameters can be assessed using a comprehensive machine learning approach. The reduced order BEM is tested using simulated data that were generated from EnergyPlus models of several buildings in Singapore.

METHODOLOGY

Figure 1 illustrates the workflow for generating reduced order BEMs to simulate interactions between buildings and their outdoor conditions at the city scale. The workflow first consists of input data that can potentially be extracted from a city digital twin platform, including a 3D city model, weather measurements, and building energy data. From the 3D city model, a sequence of EnergyPlus models of various buildings is generated, and then manually or automatically calibrated using energy data. Outputs provided by each EnergyPlus model are used to train a corresponding reduced order model. EnergyPlus models and their corresponding reduced order models use the same weather data to specify their boundary conditions. Trained reduced order models could then be coupled with the data driven UCM defined in Martin et al. (2024) to simulate interactions between buildings and their outdoor conditions at the neighborhood scale. For city scale simulations, the training procedure would need to be repeated over several group of buildings in the 3D city model for generating a sequence of coupled schemes. From the building energy consumption and outdoor conditions assessed from simulations, it would be possible to better assess climate risk of a city.

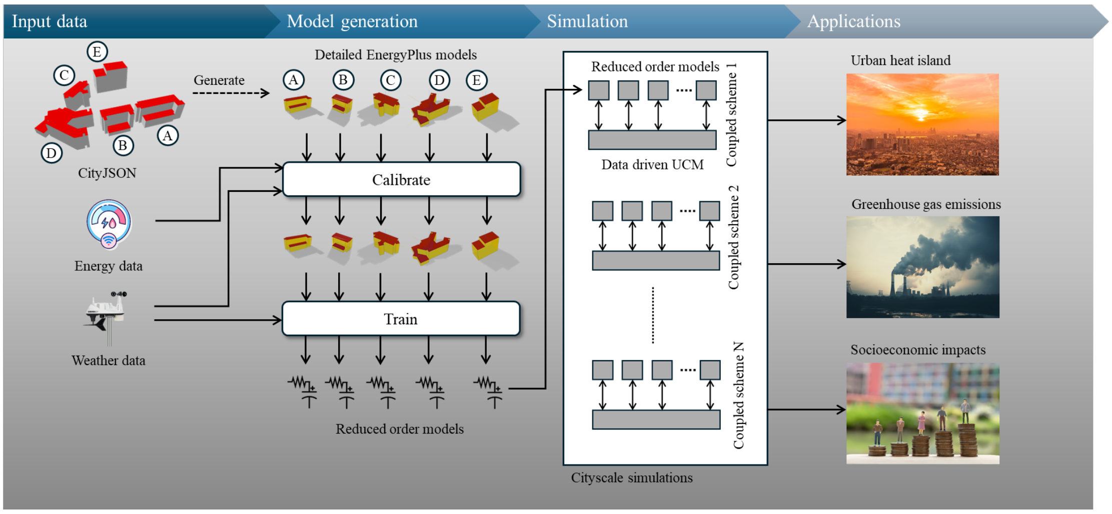

Figure 1. *Workflow to generate reduced order models for city scale simulations of interactions between buildings and their outdoor conditions.*

In this study, the Baselining, Evaluating, Action, and Monitoring (BEAM) digital twin platform was used to extract input data for generating reduced order models of buildings in a university campus of Singapore (see Figure 2). Among extracted input data, there is the geometry of five buildings, A, B, C, D, and E expressed with LOD 1.3 using the CityJSON format. Thermal properties of each building were specified from the study conducted by Martin et al. (2017) on typical office buildings in Singapore. The platform also contains weather data collected at 40 locations and the cooling consumption of each building.

As shown in Figure 3, reduced order models consist of a lumped thermal network that can predict the cooling consumption and exterior wall surface temperature of buildings. The lumped thermal network can be expressed as a linear state space model in which:

state variables are the exterior wall surface temperature ($T_{s,ext}$), the interior wall surface temperature ($T_{s,int}$), and the internal mass temperature (T_m); input variables are the indoor temperature (T_i), the outdoor temperature (T_{out}), the sky temperature (T_{sky}), the incident solar radiation ($Q^*_{sol} = \alpha_{DNI} K_{DNI} + \alpha_{DHI} K_{DHI}$), the sensible internal heat gains (H_{ihg}), the indoor specific humidity (q_i), and the latent internal heat gains (LE_{ihg}); and Outputs variables are the exterior wall surface temperature ($T_{s,ext}$), the sensible cooling load (H_{sys}), and the latent cooling load (LE_{sys}). The reduced order model assumes that indoor temperature and specific humidity remains constant at specific setpoints. Thus, it is considered that the cooling system extract the exact amount of heat to keep the indoor of the building at constant conditions. H_{ihg} and LE_{ihg} are determined based on schedules of the occupancy, artificial light, and electric equipment.

Figure 2. *Case study seen from the BEAM platform, a digital twin platform of NUS campus (CDE 2024).*

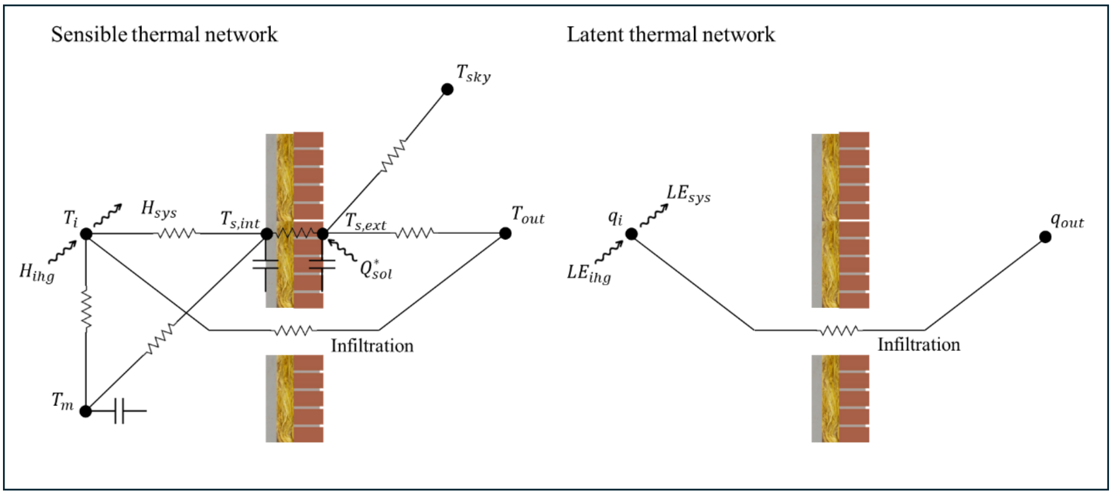

Figure 3. *Sensible and latent thermal networks for assessing the cooling consumption and exterior wall surface temperature of a building (i.e. reduced order model).*

Resistances, capacitances, and fractions of solar radiations (α_{DNI} and α_{DHI}) of reduced order models are assessed using a non-dominated sorting genetic algorithm, a comprehensive machine learning approach. The multi-objective functions were defined based on the CV-RMSE between estimated and target building energy consumption and the RMSE for the exterior wall surface temperature. It was optimized using a population size of 100, 25 offsprings, and 100 generations. Lower and upper bounds correspond to physical limits of reduced order models' parameters.

RESULTS AND DISCUSSION

Figure 4 shows the cooling consumption in buildings A, B, C, D, and E as estimated by EnergyPlus models after manual calibration and this predicted by reduced order models after being trained on a 1-month (8%) and 3-month (25%) sample. From this result, it seems that a reduced order model trained on a larger sample does not necessarily predict the cooling consumption with a lower error. While the error made by a reduced order model trained on a larger sample appears to be diminished in the case of building A, it looks to be slightly or highly increased in all other cases. It implies that a reduced order model does not need to be trained on a large sample to accurately predict the cooling consumption in a building located in Singapore.

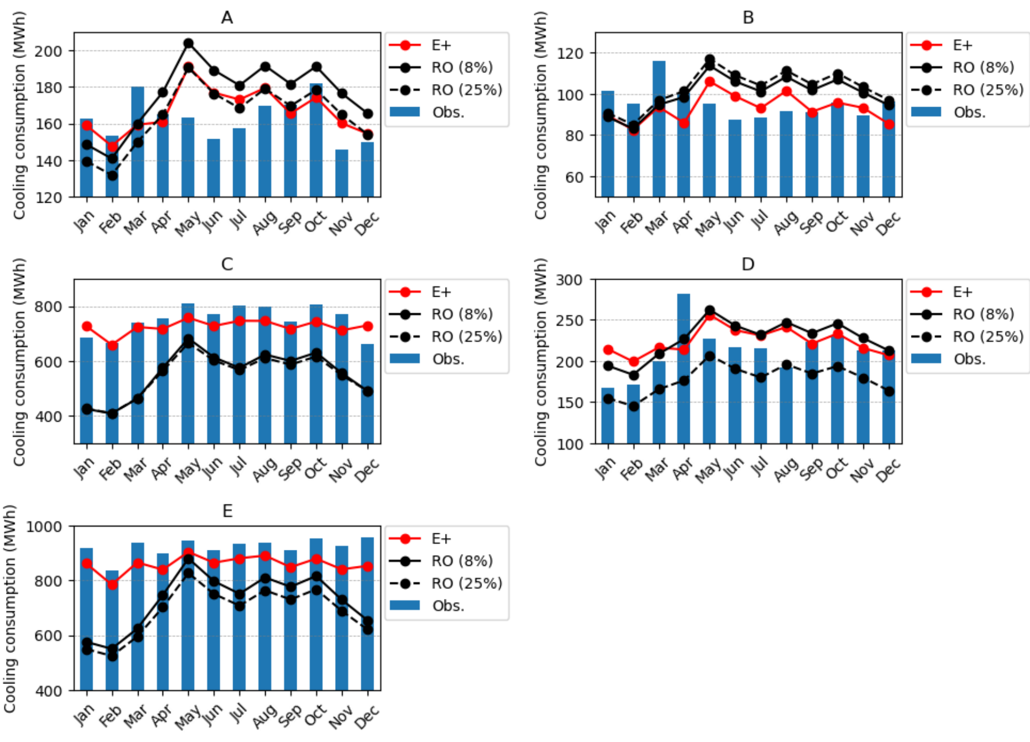

Figure 4. *Cooling consumption of buildings A,B,C,D, and E as measured from meters and estimated by EnergyPlus (E+) models and reduced order (RO) models.*

A similar observation can be made on predictions of the daily average exterior wall surface temperature as illustrated in Figure 5. In addition to that, it appears in cases of buildings C, D, and E that an overprediction of the wall surface temperature results in an underprediction of the cooling consumption. It means that in buildings where internal heat gains are more difficult to evaluate the training procedure seems to face some challenges in inferring proper physical parameters for the reduced order models.

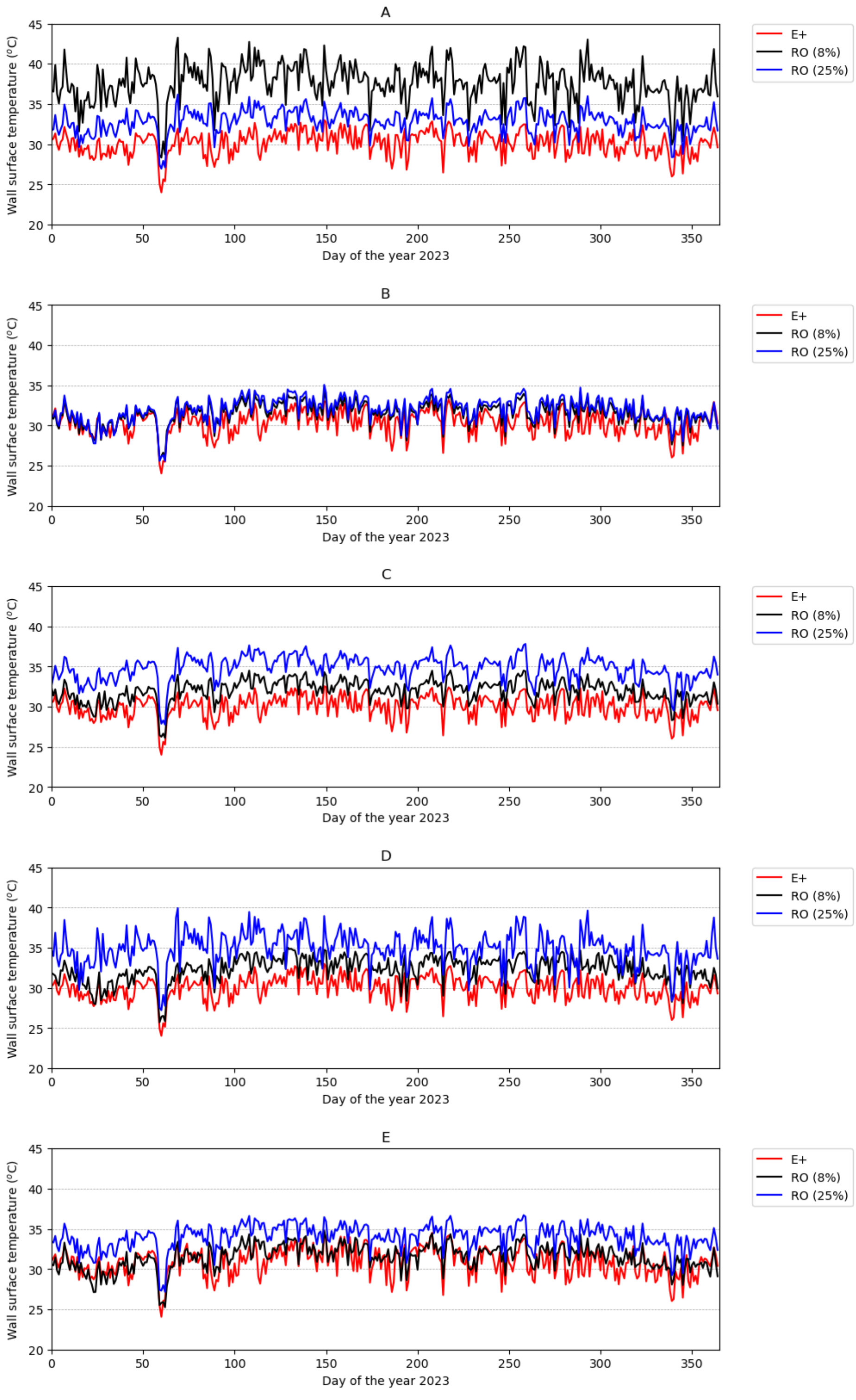

Figure 5. *Average daily exterior wall surface temperature of buildings A,B,C,D, and E estimated by EnergyPlus (E+) models and reduced order (RO) models.*

Table 1 describes the accuracy achieved by EnergyPlus models of buildings A, B, C, D, and E after manual calibration and this obtained by their respective reduced order models after being trained on a 1-month (8%) and 3-month (25%) sample. All EnergyPlus models could be calibrated under a CV-RMSE of 15% against measurements of the monthly cooling consumption. Certain EnergyPlus models, like those of buildings C and D, were more difficult to calibrate due to some uncertainties on the internal heat gains. It explains why reduced order models of these buildings achieve a lower accuracy than others. Despite these difficulties, the results show that it is possible to train a reduced order model that can predict the cooling consumption and exterior wall surface temperature with a CV-RMSE lower than 15% and a RMSE lower than 3 K, respectively, against outcomes of EnergyPlus models. It implies that reduced order models could potentially replace detailed models in the coupled scheme defined by Martin et al. (2024) for simulations of interactions between buildings and their outdoor conditions. This assertion would need to be confirmed by checking the convergence and accuracy of outcomes given by reduced order models when coupled with a data-driven UCM.

Table 1. *Accuracy of the cooling consumption and exterior wall surface temperature as estimated by EnergyPlus (E+) models and reduced order (RO) models.*

Building	*Cooling consumption CV-RMSE (in %)*			*Wall surface temperature RMSE (in K)*	
	E+	*RO (8%)*	*RO(25%)*	*RO (8%)*	*RO(25%)*
A	8.96	7.76	1.95	7.68	2.87
B	11.78	8.92	12.91	1.60	2.07
C	6.30	23.58	21.28	2.21	4.94
D	14.79	4.44	19.24	2.50	5.03
E	7.06	16.10	16.75	1.39	3.42

CONCLUSION

This paper showed a reduced order BEM whose physical parameters are assessed using a comprehensive machine learning approach. It consists of a multi objective genetic algorithm that optimizes the discrepancy of the cooling consumption and exterior wall temperature as predicted by the reduced order model and estimated by an EnergyPlus model. Before testing the reduced order models, EnergyPlus models of five buildings in Singapore were calibrated against measurements of the cooling consumption.

Results first showed that the procedure to train reduced order BEMs might vary from buildings to buildings. Reduced order models appear to achieve a better accuracy when trained on larger samples of the cooling consumption and exterior wall surface temperature of certain buildings and not others. As variations of the cooling consumption and exterior wall surface temperature depend on outdoor conditions, it is expected that reduced order models should not need to be trained on a large sample in a tropical climate like the one experienced in Singapore. However, the sample size needed to train reduced order models should certainly be larger in a seasonal climate, where outdoor conditions vary more than in a tropical climate. In the future, it would therefore be recommended to evaluate the accuracy achieved by reduced order models in different climates in addition to various buildings.

It also appeared that a good understanding of internal heat gains is crucial to train reduced order models. Indeed, internal heat gains highly determine the cooling consumption within a building. Incorrect assumptions on internal heat gains could thus result in an improper assessment of physical parameters of the reduced order models using machine learning. To solve this problem, the machine learning algorithm used to train reduced order models should give less importance to predictions of the cooling consumption when internal heat gains are highly uncertain. The priority should be to ensure that reduced order models can properly evaluate variations of the cooling consumption caused by outdoor conditions of buildings, instead of its absolute values.

Finally, it was observed that reduced order models can predict the cooling consumption and exterior wall surface temperature in good agreement with those estimated by a calibrated EnergyPlus model. Ultimately, reduced order models should be trained on measurements of the cooling consumption and exterior wall surface temperature rather than estimates provided by other models. After being trained, reduced order models could be incorporated in the coupled scheme define by Martin et al. (2024), which would also include thermal images and atmospheric weather data as input.

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