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Optimization-aided calibration of an urban microclimate model under uncertainty

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ABSTRACT

Simulation models play an important role in the design, analysis, and optimization of modern energy and environmental systems at building or urban scale. However, due to the extreme complexity of built environments and the sheer number of interacting parameters, it is difficult to obtain an accurate representation of real-world systems. Thus, model calibration and uncertainty analysis hold a particular interest, and it is necessary to evaluate to what degree simulation models are imperfect before implementing them during the decision-making process. In contrast to the extensive literature on the calibration of building performance models, little has been reported on how to automatically calibrate physics-based urban microclimate models. This paper illustrates a general methodology for automatic model calibration and applies it to an urban microclimate system. The Urban Weather Generator (UWG) is selected as the underlying simulation engine for an optimization-aided calibration based on the urban outdoor air temperature in an existing district area located in downtown Abu Dhabi (UAE) during 2017. In particular, given the time-constrained nature of engineering applications, an online hyper-heuristic evolutionary algorithm (EA) is proposed and developed in order to accelerate the calibration process. The validation results show that, in single-objective optimization, the online hyper-heuristics could robustly help EA produce quality solutions with smaller uncertainties at much less computational cost. In addition, the resulting calibrated solutions are able to capture weekly-average and hourly diurnal profiles of the urban outdoor air temperature similar to the measurements for certain periods of the year.

1. Introduction

Over the past decades, many climate projections have foreseen both global warming and sea level rise [1]. This projected climate change will potentially lead to increased food shortages, decreased fresh water supplies, and severe storm events – all of which would have a significant impact on humanity in both developing and developed regions of the world. In response to mitigating these on-going threats, the IPCC [1] urges dramatic reduction in greenhouse gas emissions and sustainable adaption of societies to a new climate context. This agenda holds a particular attention in urban areas where massive valuable assets are concentrated and more than half of the world's population resides [2]. Moreover, in some cases the anthropogenic climate change can be exacerbated by neighborhood-to-city-scale phenomena, such as the Urban Heat Island (UHI) [3].

In general, the UHI increases the peak electricity demand and likelihood of heat wave event during summer, which may cause various health problems leading to morbidity, disability, or even death [4,5]. Cities must undertake mitigation and adaptation measures to reduce the negative impacts of heat islands on the environment, the economy, and the population. However, aside from the social and economic concerns, developing effective adaptation strategies comes with a large technical challenge since an urban microclimate system comprises very complex physical relationships between many elements that may interact with each other [6]. A good understanding of the mechanism and characteristics of UHI is thus a prerequisite for decision makers to identify and adopt reliable mitigation and adaptation options, particularly during the design of new or renovated neighborhood areas.

This pressing need motivates many energy and environment research communities to expand their scope to the urban realm [7]. Great efforts have been made to incorporate the UHI effect into thermal simulations [8]. In addition, some researchers have started to examine

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Nomenclature

D	training database
$F_{E,P}/F_{E,Q}$	expensive objective and constraint values in P/Q
F_S	approximated objective and constraint values in S
$\overline{m}$	mean of the absolute measured urban-rural temperature differences
m_i	measured data point i of the urban-rural temperature difference
n	number of the data points
P	parent population
Q	offspring population
S	surrogate population
s_i	simulated data point i of the urban-rural temperature difference
t	generation counter
$w_{\mathrm{CV(RMSE)}}$	weight assigned to CV(RMSE)
w_{NMBE}	weight assigned to NMBE

Abbreviation

AEC	architecture, engineering, and construction
AM	averaged model
ASHRAE	American Society of Heating, Refrigerating, and Air-conditioning Engineers
CFD	computational fluid dynamics
COP	coefficient of performance
CV(RMSE)	coefficient of variation of the root-mean-square error
EA	evolutionary algorithm
EPW	EnergyPlus Weather
ES	evolutionary strategy
FPC	fitness prediction correlation
GIGO	garbage in, garbage out
GOF	goodness-of-fit
IPCC	Intergovernmental Panel on Climate Change
LH	Latin Hypercube
MC	Monte Carlo
MOO	multi-objective optimization
NMBE	normalized mean bias error
RSM	rural station model
SA	sensitivity analysis
SHGC	solar heat gain coefficient
SVR	support vector regression
UBL	urban boundary layer
UCM	urban canopy model
UHI	Urban Heat Island
UWG	Urban Weather Generator
VDM	vertical diffusion model

the physical behavior or causal factors of urban climate change and heat island effect via mesoscale computational fluid dynamics (CFD) simulations [9], analytical and empirical algorithms [10], and physics-based urban canopy models [11]. To account for the interactions between building energy demand and urban thermal behavior, the Urban Weather Generator (UWG) was proposed and developed by Bueno et al. [12] as a physics-based simulator to quickly estimate the microclimate condition and energy consumption at the neighborhood-to-city scale. With continuous updates and validations [13–15], the UWG has been reported to be a promising urban simulation engine with exceptionally low computational requirements.

However, despite the positive progress, simulation practice to date has only penetrated a small fraction of professional communities within the AEC industry. One recognized obstacle is the discrepancy, sometimes significant, between actual and predicted values. In general, prognostic law-driven models [16] involve a suite of simplified physical relations describing the way various component disturbances (from system operation, human activity, material property, etc.) interact with each other and influence the aggregate physical behavior. Within these equations, both differential and algebraic, hundreds of parameters exist. It is common for an engineer to make ad-hoc estimates for these parameters based on limited engineering knowledge, past user experience, and an abundance of trial and error. As a result, even though many inputs seem empirically validated, the simulated output could be far from the real scenario. It is ironic that at the time when simulation is the most popular, parameters of simulation may be the least reliable, which inevitably reduces the confidence of simulated results and curtails the use of simulation models to some extent. It is hence necessary to match simulation with measurement, a process called "model calibration."

Although some studies use calibrated models, their underlying calibration techniques are unclear. In order to dive deeper into model calibration, it is important to consider "model uncertainty" [17]. Validation of a complex-system model is notoriously difficult, especially when the purpose of the model is to look at some non-observable or unmeasured physical behavior. The reason stems from the fact that closed-loop simulations usually represent major simplifications and constraints. That is to say, "*the portion of the world captured by the model is an arbitrary 'enclosure' of an otherwise open, interconnected system*" [18]. Model errors are mainly caused by difficulties in capturing how exactly a system operates, due to software limitations and inaccurate parameter descriptions that cannot be completely modeled a priori. The input parameters are often calibrated manually by an expert, which may require days or weeks of work depending on model complexity. A commonly observed method tunes some specific parameters until the result meets an acceptance criteria without any uncertainty analysis.

Uncertainty quantification is often time-consuming and requires additional efforts in the overall design and/or retrofit phase of an engineering system, but can provide more robust decisions. However, not all the modeled aspects have the same level of importance and not every input parameter offers the same contribution to error propagation. As a result, uncertainty analysis is usually coupled with sensitivity analysis (SA) to measure the relative importance of various input parameters [19]. In general, SA is used to identify how the uncertainty in an output can be allocated to the uncertainties in the inputs. Once the "weak" parameters are determined, they could be set at some nominal values, thereby reducing the parameter space and increasing the calibration efficiency. The remaining influential input set is considered by a more rigorous calibration process.

Given that manually tuning the parameters can be viewed as an optimization process, it is natural to think about using computers to implement calibration in an automatic or semi-automatic way via optimization algorithms. Simulation-based optimization—wherein a simulation model is embedded in the optimization—has been increasingly applied in the building science community through mathematical and statistical methods to assist design analysis [20–22] and model calibration [23–25]. A pioneering study was conducted by Wright [26] in the 1980s, while the number of optimization-related papers has sharply increased since 2005 [21]. Many open-source tools, such as the GenOpt by Wetter [27], are now available to provide the capabilities of coupling various building performance simulations to effectively support optimization.

Generally speaking, an objective performance function is formulated to define a max/min target, while some constraint functions are employed to reduce the possibility of deviating too far from reality. Since the performance function associated with building or urban