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Development and assessment of simplified building representations under the context of an urban energy model: Application to arid climate environment

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ABSTRACT

For buildings in arid areas, requiring significant cooling loads, predictions of long term building cooling loads and the development of accurate Building Energy Models (BEM's) are of critical importance. However, numerous challenges and limitations are encountered in the course of generating such energy models. Furthermore, recent studies have emphasized the integration of the urban heat island phenomena in modeling building energy behavior in urban environments. This study assesses the loss of accuracy versus gain in computational effort incurred by the use of different types of simplified building representations relative to a more detailed one when applied in a building case study. The study shows that such simplification results in limited loss of accuracy, when compared to a detailed model. The RC-based simplified model reported a satisfying level of performance and was thus used to simulate the building cooling load of the case in an urban context. Furthermore, results showed an anticipated increase of cooling load demonstrating the practicality of the developed simplified model to be used in this context.

1. Introduction

Growing energy demand in high density urban areas pose a significant pressure on the economy and the social welfare of a state. Therefore, constant energy behavior monitoring of buildings, developing a well-informed energy saving strategies, and enforcing control measures to regulate supply and demand are measures of utmost importance. One such method is the thermal load prediction techniques using building energy models (BEM's).

Historically, BEM's have evolved in their complexity from basic thermal zone applications to the more advanced mathematical relations and physical modeling approaches that started in early 1970s [10,17]. There are several techniques to model the building thermal behavior and its response to internal and external resources of heat gains, where techniques may vary from simple regression models to the more detailed physically attributed models [21].

The need for intensive information input to the physical based models and the lack of comprehensive validation and verification techniques reported in literature are a major concern in this area [18]. Most of the BEM's models are validated using ideal conditions under specific range of attributes and assumptions rather than actual real-time conditions. However, the actual built environment is of high complexity and is influenced by a large number of inter-dependent variables. Hence, it is difficult to achieve an accurate representation of real-time building operations within a model simulation. As such it is crucial and challenging for the model complexity, computational requirements and the need for detailed building physical characteristics to be reduced significantly, while retaining predictive accuracy when considering reduced order building models.

Modeling the boundary conditions and the interaction of the structure with the surrounding environment is crucial for performing a sufficient analysis [17]. Whereas simulating building energy performance based on the assumption of an isolated building setting as in rural areas underestimates the actual cooling load of structures in urban settings, particularly in hot regions [1,13].

BEM's require weather data inputs as boundary conditions for energy consumption computations, which is represented by the meteorological information from weather stations [20]. These stations are typically located in rural areas, therefore, impropriate for energy simulations of buildings in dense urban cities. The effect of the anthropogenic heat gains within the urban forms, waste heat releases and solar radiation reflections on building surfaces would result in a higher temperature difference in urban regions than in rural area with the same weather conditions. These impacts cause a temperature variant on both horizontal and vertical horizons, that is, higher temperatures at lower elevations of the urban block and lower temperature in rural regions. This phenomena is known as Urban Heat Island Effect (UHI). Most of the existing building en-

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ergy models and simulation tools do not account for the consecutive effects of UHI on buildings cooling load. These shortcomings can yield significant error margins in simulations as results accuracy depend on the building location and the urban setting considered [20].

The aim of this work is to develop a simplified BEM that is capable of accurately simulating the building thermal behavior while requiring minimal amount of input data. The main fragment of energy consumption that needs to be modeled in buildings located in arid environments with high temperatures, is that attributed to cooling [11]. Accordingly, the focus of this work is on cooling load forecasting.

In order to select the best representative simplified model, several inverse modeling techniques were tested, validated and calibrated against a detailed model. The detailed model in this study serves as a replacement simulator of the actual energy consumption data that is typically used in the calibration process of such BEM's.[1] The simplified models tested in this work are; black box model (ANN), grey box model (ARMAX), white box model (RC), and a physical detailed model (EnergyPlus). The best performing simplified model was then integrated in an Urban Canopy Model (UCM) to determine cooling load penalty on the building in the case study due to UHI effect.

2. Literature review

Building energy modeling techniques that are used as predictive tools can follow either a forward based (law driven) or an inverse based (data driven) modeling approach [7]. Accordingly, the selection of the technique to be used is based on the data availability. BEM's vary based on the level of complexity, data availability, and on the followed set of laws that govern the system behavior. Most common models can be classified to engineering models, statistical models, artificial intelligence and grey models [21].

Engineering models are forward modeling technique, whereas physical principles are followed to simulate the energy behavior of the whole building as a single unit or for each sub-level component [7]. Building energy simulation tools are the common example for such modeling techniques (e.g., Energy Plus, DOE-2, ANSYS). Engineering models can be further classified to detailed or comprehensive models and simplified models, in which they vary based on the amount of input data required about the building and computational efforts. Statistical regression and artificial intelligence models are inverse modeling techniques where it requires the availability of historical data. In the Statistical regression models building energy consumption data is correlated with the most influencing variables to develop model parameters. Artificial Neural Networks (ANN) models are best used to solve non-linear problems in complex applications, where the level of complexity is based on historical data availability partially available or if there is uncertainty in the data about the building.

2.1. Simplified BEM's

Evaluation of simplified BEM's performance when used as predictive tools have been intensively performed in the literature. Li & Huang, 2013b presented a comparative assessment between four different prediction models; namely, time series (ARMAX), multiple linear regression (MLR), artificial neural network (ANN) and resistor-capacitor (RC) models in terms of precision and accuracy in determining the cooling loads of buildings. Their findings indicated that MLR and ARMAX models had the least mean bias error and mean standard deviation, while ANN had the highest mean bias error and mean standard deviation. RC networks reflected good adaptability to zone temperature set points relative to other models in consideration. Neto & Fiorelli [15] reported another comparison between Energy Plus, and ANN in predicting building energy consumption. Findings show that the energy consumption predictions provided by the energy plus model yielded an error margin of 13% for 80% of the tested data, while the ANN predictions had a relatively better performance with an average error of nearly 10%.

Kalogirou [6] studied the application of ANN as a predictive tool for passive solar buildings to simulate energy consumption. The model included five neurons in the input layer, 46 neurons in the hidden layers and 1 neuron in the output layer. The results fitted to the experimental data with a goodness of fit (R^2) value of 0.9991. Similarly, Lu, et al. (2015) [9] reported ANN applicability for calibrating numerical building models for indoor temperature estimations, in which ANN cited better performance than numerical modelling. Zhao and Magoulès [21] reported the rapid development of artificial intelligence models as it brings breakthroughs in forecasting building energy consumption.

Hudson et al., [5] presented a lumped capacitance model representation (i.e., RC network) of a high thermal capacity building elements, where a short time-scale comparison between the accuracy of a second order versus a first order was performed. The results had a good agreement with the experimental data with a first order elemental description, however, a second order model was recommended for a long time-scale analysis.

Kim & Braun [7] study provided a representation of a complex thermal network of a building envelope and its interior in the form of a set of reduced-order state space equations as an energy model-based predictive tool. This methodology resulted in a clear reduction in modeling input requirements with a 30% reduction in state variables leading to a factor of 10 reduction in the number of computations while still maintaining sufficient modeling accuracy.

2.2. Detailed engineering models

The level of uncertainty in the engineering detailed models is relatively high due the large number of parameters required to ensure accurate computations. Furthermore, these models are impractical to be used by utilities or policy makers due the lack of input data about the building physical characteristics, particularly for existing structures. On the other hand, development of simplified engineering models with basic simplified assumptions can maintain an acceptable level of accuracy as well.

Development of detailed engineering models (**DM**s) with high computational needs have been extensively debated in the past. Raftery et al. (2011) developed a detailed physical-based building energy model through an evidence-based calibration of a large office building to investigate energy conservation measures [16]. A large number of building thermal zones and measured HVAC consumption data was required and inputted to the model for increased accuracy. An exceptional correlation was achieved between the model and the measured HVAC consumption data for a particular year with a very low Mean Bias Error and Coefficient of Variation Root Mean Squared Error [4].

2.3. Urban heat island effect

Several studies in the literature had a significant contribution to the investigation of the UHI impact on the building thermal behavior. One of the first studies that have modeled the thermal interaction at an urban scale was conducted by [14], where an Urban Canopy Model (UCM) was developed. This model was further investigated by [20] and [1] in order to model the building energy consumption on a city scale.

[1] The validation of the DM was based on the availability of measured cooling load data (relevant to the case study building) for a four months period.