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Data-driven Urban Energy Simulation (DUE-S): A framework for integrating engineering simulation and machine learning methods in a multi-scale urban energy modeling workflow

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HIGHLIGHTS

- Introduces the need for urban building energy modeling and current approaches.
- Proposes a DUE-S framework that integrates machine learning and simulation methods.
- DUE-S models urban energy use on multiple spatial and temporal scales.
- Evaluates the DUE-S framework on case study of 22 dense urban buildings.
- Achieves acceptable prediction accuracies at an urban scale.

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ABSTRACT

The world is rapidly urbanizing, and the energy intensive built environment is becoming increasingly responsible for the world's energy consumption and associated environmental emissions. As a result, significant efforts have been put forth to develop methods that can accurately model and characterize building energy consumption in cities. These models aim to utilize physics-based building energy simulations, reduced-order calculations and statistical learning methods to assess the energy performance of buildings within a dense urban area. However, current urban building energy models are limited in their ability to account for the inter-building energy dynamics and urban microclimate factors that can have a substantial impact on building energy use. To overcome these limitations, this paper proposes a novel Data-driven Urban Energy Simulation (DUE-S) framework that integrates a network-based machine learning algorithm (ResNet) with engineering simulation to better understand how buildings consume energy on multiple temporal (hourly, daily, monthly) and spatial scales in a city (single building, block, urban). We validate the proposed DUE-S framework on a proof of concept case study of 22 densely located university buildings in California, USA. Our results indicate that the DUE-S framework is able to accurately predict urban scale energy consumption at hourly, daily and monthly intervals. Moreover, our results also demonstrate that the integration of data-driven and engineering simulation approaches can partially capture the inter-building energy dynamics and impacts of the urban context and merits future work to explore how they can be improved to predict sub-urban scale energy predictions (single building, block). In the end, successfully predicting and modeling the energy performance of urban buildings has the potential to inform the decision-making of a wide variety of urban sustainability stakeholders including architects, engineers and policymakers.

1. Introduction

The world is rapidly urbanizing. Over 50% of the world's population now resides in cities, and the number is expected to increase to 67% by 2050 [1]. Cities account for over 75% of all primary energy use and over 80% of gree[2,3]nhouse gas emissions, with the largest portion of such consumption (more than 40%) and related emissions coming from the built environment [2,3]. As a result, urban buildings represent a tremendous opportunity to enhance the energy sustainability of cities. According to recent estimates, as much as 90% of urban buildings are energy efficient, and up to 30% of an individual building's energy consumption is wasted [4].

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Extensive academic and industrial efforts have been undertaken to develop energy conservation measures within individual buildings (e.g., demand driven heating/cooling controls). However, building energy use is significantly affected by other buildings (e.g., shading impacts heating and natural lighting) and microclimate factors (e.g., changes in wind patterns impact heat transfer and cooling loads). A key challenge in enhancing the energy efficiency of buildings in dense urban areas is the lack of accurate energy performance prediction models that consider this urban context. Current building energy models are limited in their ability to account for the inter-building energy dynamics and interdependencies that can have dynamic and non-linear impacts on the energy use of urban buildings. Without accurate performance characterization and prediction, designers and engineers struggle to assess the energy, environmenta, and economic implications of their early-stage design and retrofit decisions, thus failing to shape a building's energy use for its entire lifecycle. This challenge is further exacerbated by adjacent buildings and the overall urban area becoming increasingly energy intensive resulting in substantial energy, environmental and monetary impacts [5–7].

Rapid growth in new sensing technologies and emerging smart city initiatives has led to an explosion of structured and unstructured data streams describing buildings and their surrounding urban environment. Simultaneously, the field of artificial intelligence is quickly developing new machine learning models that harness these new data streams to predict and characterize a wide range of physical phenomeno a within cities (e.g., air pollution dynamics [8], traffic flow [9] and energy use [10]). The primary objective of this paper is to introduce a novel Data-driven Urban Energy Simulation (DUE-S) framework that aims to bridge the gap between traditional engineering-based energy simulation models and emerging data-driven machine learning models[1]. We postulate that by integrating the two methods we can take the first step towards accurately characterizing the energy performance of urban buildings at multiple temporal (e.g., hourly, daily, monthly) and spatial (e.g., single building, block, urban) scales. These accurate characterizations can then help facilitate the assessment of design and retrofit decisions. The rest of the paper is organized as follows: Section 2 presents an overview of existing work on urban energy modeling and discusses the main gaps; Section 3 introduces the methodology of DUE-S that integrates a residual network machine learning model with engineering simulation to better understand how buildings consume energy on multiple temporal and spatial scales; Section 4 proposes the setup of a case study with 22 densely located university buildings in southern California, USA, and the measures used to validate the performance of DUE-S framework; Section 5 discusses the case study results; Section 6 outlines the limitations and future work; and Section 7 concludes the paper.

2. Background

Urban energy modeling is the virtual representation and reproduction of the energy performance for buildings located in an urban area. Generally, urban energy modeling aims to capture the urban context by simulating energy dynamics at multiple spatial and temporal scales. In this section, we provide a brief review of the existing literature on urban energy modeling: the surrounding urban context, multi-scale performance, and calibration. Finally, in order to contextualize our proposed model within the existing body of work we also provide a review of how emerging data-driven methods have been applied to the energy modeling problem setting.

2.1. Urban context

Energy is primarily consumed in buildings to smooth thermal loads (e.g., add or remove sensible and latent heat to achieve thermal balance with conduction, convection and radiation from outside and inside the building) and power loads (e.g., power lighting system, air handling equipment, computers, and other devices used by occupants). These loads are significantly influenced by the building's urban context through effects from neighboring buildings, vegetation and other urban systems [8,9,11]. For example, a building's outside temperature could be abnormally high due to urban heat island effects [12,13]. As the sun moves, the surrounding urban built environment may cast shadows and shadings that in turn impact a building's energy use [14]. Because air dynamically flows around and within buildings, wind is another key element that determines the rate of building heat transfer (e.g., convection), humidity, cooling and ventilation loads [15]. Wind speed and direction change drastically due to urban context, as nearby buildings and trees can influence wind patterns. Previous research indicates that fluid dynamics in an urban area should be included in energy modeling as it can have a substantial impact [16]. Furthermore, urban buildings can be served by district energy systems such as heating networks [17], district cooling plants [18] and energy hubs [19], making the energy use of one building highly interdependent on surrounding buildings. Lastly, the dynamics that occur in networks of building occupants can also impact urban energy use as connections and interactions among occupants have been found to vary the heating/cooling loads [11,20], lighting loads [21] and plug loads [22] across buildings.

Engineering simulation programs (e.g., EnergyPlus, DOE2, IES-VE) reproduce the physical energy processes of buildings by: (1) taking inputted building geometries and abstracting them to a network of connected nodes, (2) creating heat balance equations for all nodes across each hour of a virtual year and (3) solving those equations within each time step, using many assumed non-geometric building parameters to calculate a building's energy consumption. However, because there are a large number of nodes to model and equations to solve, simulating the performance of hundreds of buildings across a city at once is both time intensive and computationally expensive [23]. Efforts have been made to simplify this modeling process. Specifically, the geometries can be extracted from GIS (Geographic Information Systems) [24,25], CityGML [26], BIM (Building Information Modeling) [27], CAD (Computer Aided Design) [28] or digital images [29]. Additionally, non-geometric properties (e.g., building and construction material, operation schedules, HVAC systems) have been assumed based on "archetypes"—templates representing groups of buildings with similar properties—to reduce the number of input variables [23,27]. In order to define "archetypes," buildings are divided into groups based on properties like shape and age where buildings within each group are considered identical. While highly productive in reducing the amount of input variables into an energy simulation model, the characterization of "archetypes" is often ad-hoc and depends greatly on the availability of data [11]. As a result, it is often difficult to evaluate the reliability and authenticity of the results. New "hourglass" approaches [30,31] have begun to address some of the shortcomings of archetype-based models as they combine reductive archetype models with a re-diversification process in order to add stochastic variations to individual buildings and re-introduce diversity lost in the reductive archetype process. Moreover, reduced-order methods have also been developed to model urban energy use, including electrical circuit analogy based on resister-capacitor networks [32], energy demand calculations based on quasi-static monthly energy balance [33], degree-day estimations based on heat transfer coefficient [30], steady-state methods based on energy balance equations [17], thermal shoebox models based on insolation analysis and clustering [28] and reduced-complexity models based on simplified state space methods [34]. However, such reduced-order methods often require large over-simplifications (e.g., a building is modeled as single thermal zone) [28]

[1] The short version of the paper was presented at ICAE2017, Aug 21–24, Cardiff, UK. This paper is a substantial extension of the short version of the conference paper.