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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 greenhouse 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 [11–13]. For example, a building's outside temperature could be abnormally high due to urban heat island effects [14,15]. As the sun moves, the surrounding urban built environment may cast shadows and shadings that in turn impact a building's energy use [16]. 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 [17]. 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 [18]. Furthermore, urban buildings can be served by district energy systems such as heating networks [19], district cooling plants [20] and energy hubs [21], 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 [22,23], lighting loads [24] and plug loads [25] 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 [26]. Efforts have been made to simplify this modeling process. Specifically, the geometries can be extracted from GIS (Geographic Information Systems) [27,28], CityGML [29], BIM (Building Information Modeling) [30], CAD (Computer Aided Design) [31] or digital images [32]. 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 [26,30]. 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 [13]. As a result, it is often difficult to evaluate the reliability and authenticity of the results. New "hourglass" approaches [33,34] 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 [35], energy demand calculations based on quasi-static monthly energy balance [36], degree-day estimations based on heat transfer coefficient [33], steady-state methods based on energy balance equations [19], thermal shoebox models based on insolation analysis and clustering [31] and reduced-complexity models based on simplified state space methods [37]. However, such reduced-order methods often require large over-simplifications (e.g., a building is modeled as single thermal zone) [31]

[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.

and require making several strong assumptions (e.g., the heating set point is constant) [19].

Ongoing research to quantify the impact urban context has on building energy use has been primarily focused on modeling microclimatic factors alongside simulation. Several studies have quantified the effects radiation exchange has on building energy consumption. For example, ENVI-met, a three-dimensional microclimate model, has been integrated into EnergyPlus in order to quantify the interactive effects of CFD (Computational Fluid Dynamics) and thermodynamics on building energy consumption [38,39]. Other tools such as the Urban Modeling Interface (UMI) are focused on modeling conditions such as shading and urban heat island effects in addition to energy use within the context of urban planning [40]. So while new tools [16,41] are emerging that begin to incorporate some aspects of building interdependencies in dense urban areas and model the impact of energy retrofits, there remains a significant opportunity to develop new approaches to comprehensively capture all the influences of the urban context in building energy modeling.

2.2. Multi-scale performance

Accurately characterizing and modeling the energy performance of urban buildings on multiple scales is integral to gaining a comprehensive picture of the impact of early-stage design decisions and energy efficiency retrofit solutions. For example, insights from accurate building scale models can inform building operations and energy efficient building management [42]. Block scale modeling can reveal insights on how design changes (e.g., proposed building heights and orientation) impact solar shading on other buildings and facilitate block scale optimization of energy use [11]. Urban scale modeling can support decision-making regarding sustainable zoning and other planning guidelines that impact a city's overall morphology and subsequent energy use [43]. As a result, in order to maximize the use cases and facilitate more holistic sustainability and energy decision-making, it is integral that urban energy performance simulations are accurate on multiple scales.

Engineering modeling methods are powerful at simulating a single building with a standalone HVAC system [44] but fail when applied beyond a single building [45]. Even co-simulation, like the coupling of EnergyPlus and Modelica [20], faces difficulty in generating reliable simulation results at multiple scales. Similarly, reduced-order modeling methods are limited to the scale at which they are built and are not extensible to other scales. In order to overcome this issue, various methods for scaling single building simulations have been developed. These scaling methods include: using a single aggregated building to represent all individual buildings in a district [46], multiplying energy use of a single building by the number of buildings per archetype [26], scaling up results of an individual building model by a floor area weighting function [47] or adding up the energy use of individual buildings to represent the larger scale energy use [19]. While such scaling methods have enabled some modeling and characterization of urban energy use, they struggle to achieve highly accurate results at multiple scales simultaneously in a single comprehensive model. Even the prevailing bottom-up methods using a set of calibrated and validated archetypes [48] have limited capability to model energy use accurately at multiple scales as the numbers, characterization and representativeness of archetypes differ dramatically across scales.

Previous work [49] has shown that the high accuracy of an energy model at one scale does not guarantee high accuracy at others as the impacts of urban context are highly variable across scales, especially when the microclimate varies spatiotemporally. Obtaining high-modeling accuracy at multiple scales simultaneously becomes increasingly difficult as the complexity exponentially increases due to the nonlinear interactions and interdependencies from thermal equilibrium, geometry, fluid dynamics, occupant networks and system responses within urban buildings. While previous work has demonstrated positive results at both district and building scales [19,50], such models have limited predictive ability to quantitatively estimate the impacts that design and/or retrofit changes in one building (e.g., new HVAC control strategy) have on the energy use of surrounding buildings. As a result, this paper aims to build upon previous work by proposing and validating an urban energy modeling framework that is capable of modeling energy performance at multiple scales (single building, block, urban).

2.3. Energy modeling calibration

Simulation is a context-related process, and results from uncalibrated models can deviate significantly (up to 90%) from actual energy use [51,52] – making calibration indispensable before any practical use can be made of the results. Urban energy modeling calibration is an inverse approximation as it requires the reconciling of simulation outputs with measured energy data. It is often over-parameterized due to the large number of independent and interdependent input parameters and assumptions that must be specified. Because the inverse and over-parameterized characteristics of calibration could be naturally associated with misassumptions of building energy dynamics, they are some of the main drivers of uncertainty in the energy modeling process [53]. In order to overcome these issues, researchers [54,55] have utilized an iterative process to adjust input parameters and assumptions based on available data during the modeling process until the discrepancies between simulated results and measurements are within the ranges regulated by practice standards [56,57]. This genre of methods follows the trial-and-error principle or Bayesian update that requires significant time and effort as the performance of the energy model depends largely on ad-hoc data availability and subjective engineering judgment [58,59]. Another type of calibration focuses on applying statistical analysis to find the relationships between input parameters and actual energy use during the modeling process [60,61]. The input parameters can either be static (e.g., window-wall ratio) or dynamic (e.g., zone temperature). While this approach is computationally efficient and can enhance the accuracy of energy simulation models that consider the urban context [62], retraining with additional ground truth data is required if any changes are made to a building (e.g., building envelope retrofits), building system (e.g., HVAC control upgrades) or the surrounding urban environment (e.g., new buildings). More importantly, since the statistical relationships are constructed on a building-to-building basis and utilized to adjust simulation inputs, they can be overspecialized and may lack generalizability to other buildings and urban areas, and thus limit their applicability for modeling urban energy use at multiple scales.

2.4. Emerging data-driven approaches to urban energy modeling

The advent of smart meters and open data initiatives across major cities has made energy data available in varying spatial and temporal resolutions. This data availability combined with the rapid development of new data-driven machine learning models has spawned the use of computational intelligence to find hidden patterns of urban building energy use. As a result, these emerging data-driven energy models are able to achieve high degrees of accuracy and quantify the impacts of various energy covariates, such as building characteristics, weather, spatial patterns or use types [63]. Common models utilized in previous work to predict building energy consumption include multiple linear regression models [64], support vector regression [65], decision trees [66] and artificial neural networks [67]. Specifically, support vector regressions are kernel-based algorithms that excel when solving non-linear problems and have been applied to model the energy use of multi-family residential buildings [10]. Decision trees are a subset of flexible algorithms that divide features into weighted branches to make predictions [66], and artificial neural networks are non-linear models that use interconnected neurons and activation functions to relate

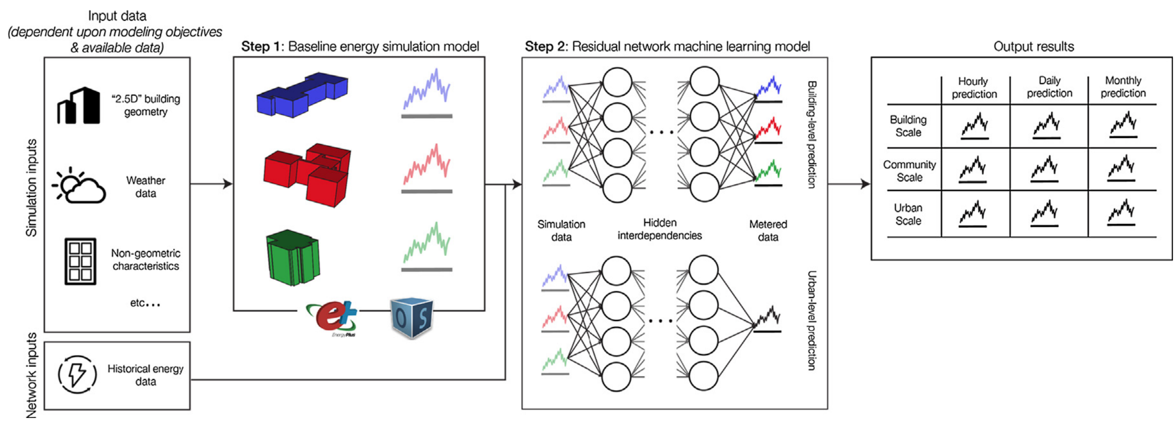

Fig. 1. Proposed DUE-S modeling framework. Step 1 uses information from existing data sources to create individual building energy simulations. Step 2 employs a residual network model (ResNet) to predict the metered energy use by learning the uncertainties of the building energy simulations and their surrounding urban environment.

input, hidden and output layers of information [67]. Tso and Yao [68] compare the performance of decision trees, neural networks and multiple linear regression models to predict residential energy consumption in summer and winter seasons and find that both decision trees and neural networks perform well in this task. Unfortunately, the majority of these studies focuses exclusively on creating models to predict individual building energy use and have yet to explore how such methods extend to the urban context.

Recent work that has evaluated building energy use at the urban scale has been largely done for benchmarking or energy mapping purposes [69]. Clustering methods are used to divide large groups of buildings into sub-groups based on common features in order to evaluate them against a baseline building level [70]. Artificial neural networks have also been used on the multi-building scale to evaluate the energy consumption of schools and office buildings [71,72]. And while one study was able to apply ordinary least squares, random forest and support vector machines to predict building energy use with public data provided by energy disclosure policies, its results were limited because the temporal granularity of the data was only provided at the annual scale [73]. However, there is now increasing popularity for employing complex deep learning-based models that can take better advantage of the vast amounts of available data and improved computational power of GPUs and CPUs. Deep learning is the process of training neural networks, which are able to take a set of input features and figure out functions that map them to labeled predictions. Neural networks are modeled similarly to how neurons input, process and output information in the brain through a hierarchy of hidden layers. They are trained to perform a specific function by using a non-linear activation function to calibrate the weights of connections between neurons, also called "nodes," with the goal of minimizing a loss function, typically through gradient descent [74]. Deep learning has previously been applied to a wide variety of fields related to the urban built environment including forecasting solar and wind consumption [75], predicting traffic flows [76] and forecasting building energy consumption [77]. Specifically, convolutional neural networks (CNNs), which are characterized by their locally connected layers, have been used to represent the spatio-temporal nature of traffic flow [76]. CNNs have also been applied to individual building energy forecasting because of their ability to represent time series data in a grid topology [77]. In addition to CNNs, recurrent neural networks (RNNs) are also popular for time series forecasting because they use previous predictions as additional inputs for future ones. This type of model, for example, has been used to forecast wind speed for a network of wind stations [75].

While purely data-driven approaches are able to model the statistical relationships between building energy use and characteristics [67], they rely too much on the mathematical patterns in available data without considering any underlying physics of building thermal and energy systems. Therefore, pure data-driven approaches lack the ability to accurately estimate the energy implications of early-stage design or new retrofits to buildings (e.g., installation of a new window material) that are not included in the training dataset. Since buildings in an urban area could have hundreds of possible design and/or retrofit changes, it is impossible to have a robust dataset for training an algorithm that encapsulates all potential options. As a result, this paper aims to bridge the gap between emerging data-driven machine learning and engineering energy simulation methods by proposing a Data-driven Urban Energy Simulation framework (DUE-S). DUE-S aims to integrate engineering simulation models with new data-driven machine learning models to enable the exploration of potential early design decisions and energy conservation measures while capturing the non-linear and complex interactions of the urban context. It is this novel integration of engineering and data-driven methods that we postulate enables the DUE-S model to accurately characterize and model the energy performance of buildings at multiple spatial and temporal scales. Furthermore, we clarify that our objective is not to propose an alternative for calibration of energy simulation model inputs with new data streams but to utilize a data-driven approach that learns the complex relationships and patterns of urban building energy use.

3. Methodology

In this section, we describe the mechanics of the DUE-S model—a two-step process that aims to integrate engineering-based and data-driven approaches, as shown in Fig. 1. This first step is to build baseline energy simulation models with an appropriate level of detail based on analysis of the tradeoffs between the modeling objective and availability of data (Step 1). The desired output of this step is periodic time series data for each building that captures its basic energy processes and use patterns. Subsequently, these time series become the structured data inputs to the residual network (ResNet) machine learning model (Step 2), where we use the machine learning algorithm to learn the relationships between the simulated and actual metered energy data for each building. The final output of the DUE-S model is an integrated urban energy model that can be utilized to predict and characterize the performance of buildings at multiple temporal and spatial scales.

3.1. Step 1: Baseline energy simulation models

Energy simulation is often over-parameterized and, if generated on a larger, urban scale, requires an infeasible amount of time and resources to accurately complete. The data available to create model inputs for each individual building varies drastically from building to

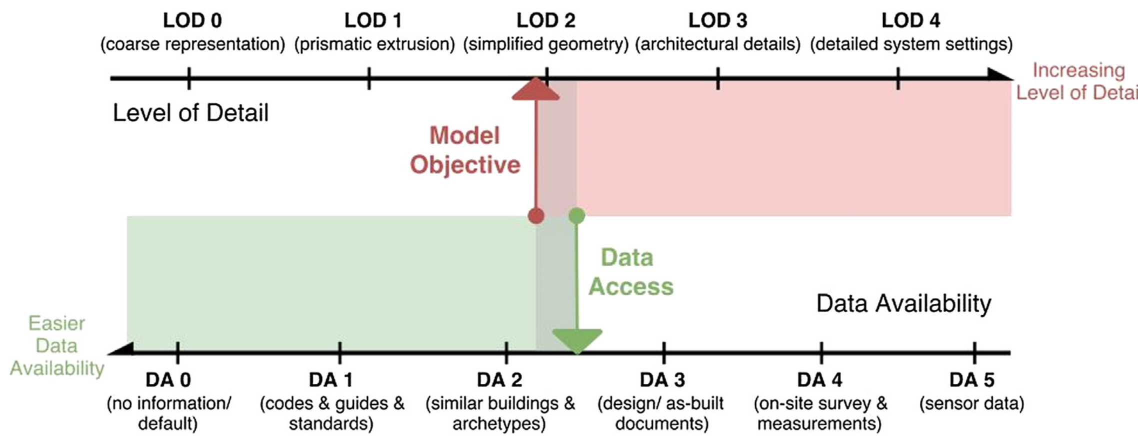

Fig. 2. Determination of model input based on the tradeoffs between the level of detail and data access.

building due to numerous factors ranging from the time period in which it was built to privacy concerns. As a result, it is important that a consistent level of detail across an entire target urban area should be determined for developing baseline energy simulation models in Step 1 of our proposed DUE-S framework. In order to do this, we first must determine the required level of detail and generate energy simulation models with at least this level of detail for each building in the urban study area.

In general, there is a tradeoff between the level of detail needed for an energy simulation and the resources needed to acquire the required supporting data. Specifically, the level of detail is associated with a model's performance and uncertainty. A higher level of detail could result in more accurate simulation results, however, could also require more precise building-related data. Different purposes of urban energy modeling require different levels of uncertainties from model input (e.g., the design of a new building envelope does not need detailed occupancy schedules as the building has not been occupied yet). The energy modeling objective is the critical value to determine the minimum level of detail (red arrow in Fig. 2). Details below the critical value are required at minimum to be actual in order to build the baseline energy models. On the other hand, the data access required to construct such details also needs to be considered. The scale of data availability regulated is represented in Fig. 2, where lower-level data is considered less reliable than higher-level data for determining input parameters and assumptions but is easier to collect [78]. The critical value (green arrow in Fig. 2) indicates the minimum level of data that is easily accessible to modelers (green zone in Fig. 2). As a result, the shaded grey region in Fig. 2 represents the model input determination that weighs the tradeoff between the level of detail required for the modeling objective (e.g., retrofit analysis, pre-design phase) and the availability of data (e.g., GIS shapefiles, sensor-based data) for developing models.

To be clear, the exact locations of critical values for the level of detail (red arrow in Fig. 2) and for data access (green arrow in Fig. 2) vary case by case, thus the final level of generalization of the energy model can differ. In this paper, it is assumed the objective of our urban energy model is to test the impacts of geometric designs and physical efficiency retrofits on building energy use in a dense urban area. Based on the analysis of tradeoffs between the level of detail input and data access, the baseline energy simulation models require the inputs of the following data primarily collected from publicly available datasets: weather, building shape, building height and number of floors. To model a site's climatic conditions, energy simulations often rely on Typical Meteorological Year (TMY) datasets, which contain the "most average" hourly weather information for a site, including variables such as dry bulb temperature, relative humidity, solar radiation and wind speed [79]. However, with the increasing availability of historical weather data at the hourly interval [80], this can be substituted in place of a more generalized TMY file.

We use the building GIS shapefiles available from local municipal websites to construct building geometries. The data structure normally contains fields on building IDs, height, elevation and roofline area. By merging this information with the shapefiles in SketchUp, simplified massing models—often referred to as "2.5-D" models—can be constructed for each building to understand its area and orientation. The buildings can be further divided into floors using either additional information or calculations based on standard floor-to-floor height. Finally, the non-geometric building properties, which include the building's systems, schedules and internal constructions, must be defined. Since these fields are above the critical value of level of detail defined by our model's objective, we define input parameters based on the U.S. Department of Energy's (DOE) Commercial Reference Building models [81]. The DOE and several of its national laboratories used national data from the 2003 Commercial Building Energy Consumption Survey (CBECS) to determine an average mix of representative buildings. These reference models include 16 building types for 3 different construction periods and represent about 60% of the U.S. commercial building stock. Each of these models is available as a ZIP file with detailed spreadsheets of plug and process loads, construction assemblies, operating schedules and systems. In the case that certain non-geometric parameters are available for a specific urban area per open data initiatives, they can be used in place of the more generalized Commercial Reference Building inputs. Other input parameters that are not specified by the reference models or publically available datasets are given default values by engineering simulation tools like EnergyPlus. We acknowledge that different simulation programs (i.e., IES-VE, DOE-2, ESP-r) use varied default values as input parameters and rely on varied assumptions about thermal dynamics and energy processes to create an energy model. Theoretically, modeling the same building in two separate energy simulation programs would result in different results. However, this won't impact the overall performance of DUE-S, as the goal of first step in DUE-S is only to capture the baseline energy usage dynamics of each building based on the tradeoffs between the modeling objective and data availability (see Fig. 2). The second step of DUE-S and its residual network, discussed subsequently in Section 3.2, will further capture the remaining uncertainties about the generalized inputs and the impacts of urban context. As a result, DUE-S is agnostic to the simulation programs used to create the underlying baseline energy models.

Once all data primary inputs for weather, geometry and non-geometric parameters are ready [82], multi-zone thermal models are created using OpenStudio, the EnergyPlus plugin for SketchUp. The 2.5-D massing models are constructed and divided into a pre-determined number of floors. Each floor is further divided into core and perimeter thermal zones, per ASHRAE 90.1 Annex G [83]. Each building is assigned an archetype (one type of U.S. Commercial Reference Building model) based on building age and use type. Finally, each individual building is simulated in EnergyPlus, resulting in an output of an IDF file and a time series of 15-min interval electricity use. We stress that the goal of these energy simulation models is to control their uncertainties from input parameters by analyzing the tradeoffs between the modeling objective and data availability, in order to capture the basic energy use dynamics of each building. The outputs (i.e., simulated energy use) of this step will then serve as inputs for the second step of the DUE-S modeling workflow: the residual network machine learning model.

3.2. Step 2: Residual network machine learning model

We theorize that the primary sources of uncertainty in building energy modeling arise from both the assumptions made in the energy simulation process as well as the "hidden" urban context impacts that are not captured by individual energy simulations. By using a deep learning algorithm to map simulated energy consumption to its actual building energy consumption, we expect this model will better account for the uncertainties in both the input parameters and assumptions and the urban context. More importantly, because interdependencies between buildings and the surrounding environment are dynamically coupled, the impact of the urban context takes a non-linear form and as a result can benefit from a deep network architecture that utilizes multiple hidden layers to capture this non-linearity.

In selecting a deep learning algorithm, we wanted to take full advantage of the spatial nature of the dense urban built environment, which a convolutional neural network and its locally-connected layers would be particularly efficient at handling. While time series forecasting is more commonly done using sequence models such as recurrent neural networks, past studies have employed CNNs and shown their ability to outperform these other models [76,77,84]. However, CNNs with very deep networks can also suffer from degradation (i.e., a saturation and rapid decline in training accuracy) [85]. This occurs when the information passed between convolution layers is not well estimated, which results in a "snowballing effect" of inaccurate predictions based on the poor performance of one layer. Residual networks (ResNets)—an extension of CNNs—apply convolutions in a similar manner to traditional CNNs but do not experience the high training losses associated with degradation. Both deep and shallow ResNets have been previously used in a spatiotemporal context to model crowd flow prediction [86] and have been shown to outperform traditional deep CNNs [87].

ResNets are a type of deep convolutional neural network made up of a series of residual blocks, as shown in Fig. 3a. An exhaustive explanation of residual networks and their architecture can be found in [85,88]. A residual block is made up of two convolutional layers and an identity mapping "skip" connection $\boldsymbol{a^{[l]}}$ that can pass over layers to a deeper location in the neural network [88]. It is this "skip" connection in the ResNet architecture that makes it uniquely applicable to the context of urban energy modeling and the primary reason for choosing it in our initial testing of the DUE-S framework over other machine learning models. First order impacts of the urban context on energy use (e.g., shading) are captured by the traditional connections between layers in the ResNet. The "skip" connection enables the ResNet to learn the complex second-order impacts of surrounding buildings (e.g., thermal radiation, coupled occupant dynamics) of which may impact some buildings but "skip" buildings that are not impacted. As a result, the "skip" connection could enable the ResNet to capture the complex second-order effects of the urban context without forcing the model to over fit on a single layer and cause degradation (see Fig. 3b).

Specifically, as $\boldsymbol{a^{[l]}}$ skips through the first layer of the residual block, it passes through a linear function and a non-linear activation function:

$$Z^{[l+1]} = W^{[l+1]}a^{[l]} + b^{[l+1]}$$

$$a^{[l+1]} = g(Z^{[l+1]})$$

where $\boldsymbol{W}$ is the matrix of learned parameters for the ResNet, $\boldsymbol{a}$ is the activation for layer $\boldsymbol{l}$, $\boldsymbol{b}$ is the bias vector, and $\boldsymbol{g}$ is the activation function. This process is then repeated through the second layer in the residual block, except for the newly introduced skip connection, which adds the original input information, $\boldsymbol{a^{[l]}}$, after the linear function but prior to the second non-linearity equation:

$$Z^{[l+2]} = W^{[l+2]}a^{[l+1]} + b^{[l+2]}$$

$$a^{[l+2]} = g(Z^{[l+2]} + a^{[l]})$$

Batch normalization is often included as part of the ResNet architecture in order to more easily tune its hyperparameters and train the neural network [89]. The specific architecture of a residual block may vary depending on application, but we designed the residual block for this framework based on the results of [88] (Fig. 3b).

The overarching goal of the residual block is to learn the mappings between $\boldsymbol{a^{[l]}}$ and $\boldsymbol{a^{[l+2]}}$ while avoiding the issue of degradation. The output of the ResNet is the final prediction for building energy consumption, which, depending on the network architecture, could be at any time interval (e.g., hourly, daily, monthly, annually) or spatial scale (e.g., individual building, block, urban scale).

4. Case study

4.1. Study area and data inputs

To test the performance and feasibility of DUE-S, we draw data and information from an urban university campus located in California, USA. Because one of the goals of DUE-S is to capture how inter-building energy dynamics affect energy use, this site was selected based on the dense network of buildings on its campus. The study area (Fig. 4) is comprised of 22 university buildings, located on 4 adjacent blocks used primarily as offices and classrooms. We note that while the DUE-S model works for multiple energy types, this case study specifically analyzes electricity use as this data was only available and the most relevant for energy loads in the moderate climate of California, USA. A typical daily, monthly and yearly load profile for a building in the case study is provided in Appendix A. Its surrounding area contains additional buildings not included in this study and is paved for both car and pedestrian traffic with additional landscaping. As shown in Table 1, the data used to inform the baseline energy simulations was gathered through both publicly accessible datasets and the local university facilities department. We gathered three years of hourly historical weather data on the specific study area from the National Oceanic and Atmospheric Administration (NOAA) [80] and utilized this data for each year of simulation. To create the building geometries, we drew from a building GIS shapefile provided by Los Angeles County's LARIAC (LA Region Imagery Acquisition Consortium) program [90]. Since all the 22 buildings were built before 1980 and mainly consist of offices, the non-geometric properties for each building were defined based on the DOE Commercial Reference Building's "pre-1980s" construction and "medium office" use type. Additional interviews with a university facility manager defined the window-to-wall ratio (WWR) to range from 0.3 to 0.4. While BIM was available for some of the buildings on campus, we were more interested in evaluating the accuracy of DUE-S given fewer detailed inputs, as this would more likely be the circumstance facing an energy modeler on a city scale.

After simulating each of the 22 buildings for three years, each of their resulting 15-min interval time series of electricity consumption become the inputs to our residual network model. For our implementation of the ResNet, we shape our input data—the simulated data—into 1095 daily signals of 96 15-min time steps for all 22 buildings (Fig. 5). This input tensor with dimensions [22, 1095, 96] was then flattened to a 2D matrix of size [22, 105120] to feed into the

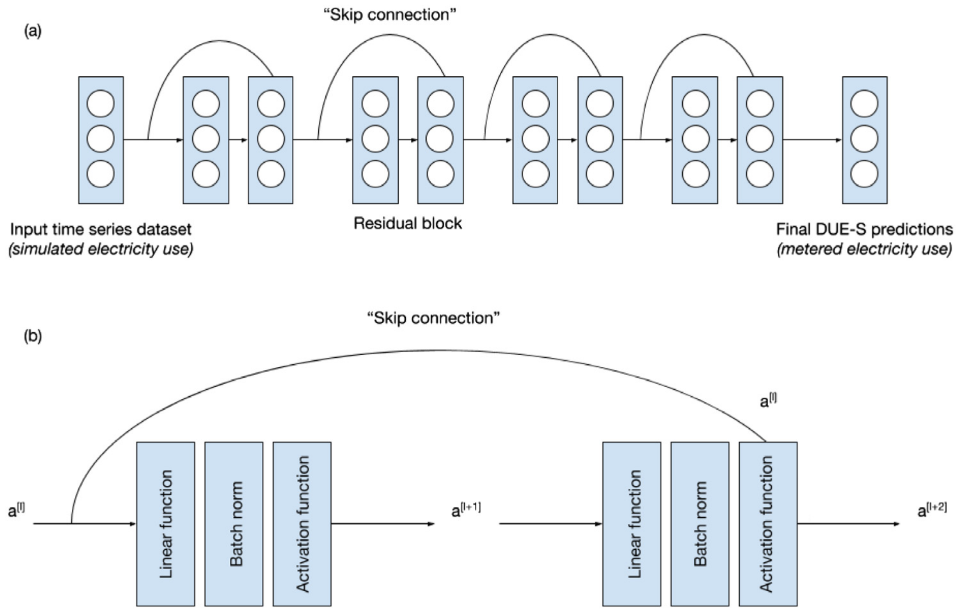

Fig. 3. a (top). General ResNet architecture. Inputs to the model consist of periodic time series representing simulated energy use. These inputs are passed through a series of residual blocks that aim to learn the hidden relationships between simulated and metered energy use. b (bottom). Architecture for DUE-S ResNet residual block. Each residual block contains a series of convolution layers, batch normalizations and non-linear activation functions.

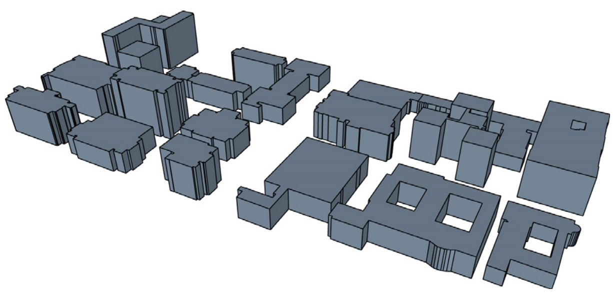

Fig. 4. Test bed study area for DUE-S.

Table 1
Datasets and data fields used for DUE-S baseline energy simulations.

Use	Data source	Data type	Data field
Building geometry	LA Region Imagery Acquisition Consortium (LARIAC)	Shapefile	Building area Building height Building elevation
	Client	Interviews	Num. of floors Average WWR Other specified non-geometric parameters
Weather data	NOAA	Time-series datasets	Historical hourly weather information
Non-geometric parameters	DOE Commercial Reference Building (pre-1980s medium office)	Database	Occupancy schedules Building constructions HVAC type Heating/cooling loads

ResNet. We then one-hot encode, or featurize, *day of the week* (7) and *month* (12) into our input space, increasing the number of input features to 41 while keeping the number of output features at 22 for a final flattened matrix of dimension [41, 105120]. We then split our data into training, development and testing sets. The training set, which is made up of 60% of the total data, is used for training several iterations of the ResNet—each of which use different combinations of hyperparameters (e.g., number of hidden layers, number of hidden units per layer, learning rate and activation function). The development set, which is made up of another 20% of the total data, is used to evaluate each of the models developed with the training set and to prevent overfitting when evaluating on the test set. Finally, the testing set, which contains the last 20% of the data, is used to evaluate the overall accuracy of the ResNet.

The training inputs were initially fed through a 1D convolutional layer that output 64 channels, determined through trial-and-error experimentation of three different channel sizes (32, 64, 128). These 64 channels were then passed through 8 residual blocks, each of which contain two 1D convolution layers, batch normalization and a leaky ReLU non-linear activation function with a coefficient of leakage $\alpha = 0.01$, as shown in Fig. 3b. The number of residual blocks and activation function were chosen using an exhaustive trial-and-error tuning process. These 64 channels were passed through a final 1D convolution to output 22 channels, which were then fed through a fully connected logistic layer and a linear output layer, each containing 22 hidden units, to produce the final prediction for DUE-S. To optimize the network parameters, we used the Adam optimization algorithm to minimize MBE [91]. The ResNet's architecture was adjusted to evaluate the prediction accuracy of DUE-S at the individual building, block level and urban level, and the results are discussed in Section 5.

4.2. Validation metrics

The performance of DUE-S depends on how reliable the simulation results match the actual electricity use. To evaluate the accuracy to which our model predicts the electricity use at the individual, block and urban scales, we compare the predicted electricity consumption to the metered electricity consumption at hourly, daily and monthly intervals using MBE, CV(RMSE) and MAPE. The first evaluation metric is the Mean Bias Error (MBE):

$$MBE = \frac{\sum_{i=1}^{n} Y_i - \widehat{Y}_i}{\sum_{i=1}^{n} Y_i}$$

In this equation, Y_i is the actual measurement of energy use and $\widehat{Y}_i$ is the simulated value; n is the number of measurements (this varies by time interval being studied with $n = 1095$ days, 36 months or 3 years in our case study). MBE is a non-dimensional metric for overall deviation, which can effectively reflect overestimation versus underestimation. It measures long-term model performance through analyzing the error between the simulated and measured energy use intensity.

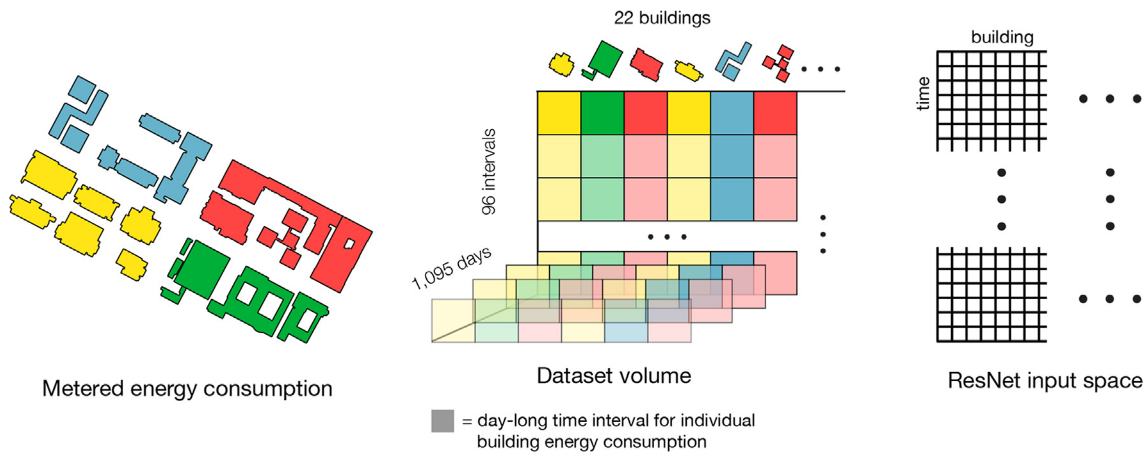

Fig. 5. ResNet input space and dataset volume. After simulating each of the 22 buildings, the time series data was shaped into an input volume of 22 buildings × 1095 days × 96 15-min intervals of energy consumption. This volume was then flattened to become the 2-dimensional input space used in the ResNet model.

The second metric is the Coefficient of Variation (CV) of RMSE (Root Mean Square Error):

$$CV\,(RMSE) = \frac{\sqrt{\sum_{i=1}^{n} (Y_i - \widehat{Y}_i)^2}}{(\sum_{i=1}^{n} (Y_i))/n}$$

The CV(RMSE) is determined by dividing the RMSE by the mean measured energy use intensity. It is not influenced by the compensation effect and can evaluate the variability of agreement between the simulated results and measured values over a period of time.

Finally, we evaluate the accuracy of the DUE-S case study using MAPE (Mean Absolute Percentage Error), which is a common metric used to evaluate the percentage error for forecasting applications:

$$\text{MAPE} = \left(\frac{1}{n}\sum_{i=1}^{n}\frac{|Y_i - \widehat{Y}_i|}{Y_i}\right)*100$$

In previous studies, the time granularities of comparison include hourly [92], daily [93], monthly [94], yearly [19,95] and even aggregated value for the entire period [36]. However, the comparison is only limited for a few buildings in a small district due to the lack of available data. A comprehensive comparison at different spatial levels for validation is missing – a feature DUE-S is able to provide.

5. Results and discussion

After running the complete DUE-S framework for the case study buildings, we calculate the Mean Bias Error (MBE), Coefficient of Variation (CV) of RMSE and Mean Absolute Percentage Error (MAPE) per the equations discussed in Section 4.2. We note that the errors across our training, development and test data sets were consistent (e.g., monthly urban predictions had MAPE of 5.32%, 6.41% and 8.28% for training, development and testing datasets, respectively) and indicate that our ResNet model did not overfit to specific time period of the training data. The overall results are provided in Table 2 for all assessed spatial and temporal scenarios. To calculate the error results, we first aggregate the data temporally across all buildings to the desired scale for analysis (e.g., hourly, daily, monthly). Then, depending on the specified spatial scale, we aggregate the results, if necessary, to the block or urban scale.

In order to contextualize our results, we compare them to the ASHRAE Standard Guideline 14 [56], which defines metrics and guidelines for hourly and monthly building energy modeling for individual buildings. While ASHRAE currently does not have a standard to evaluate prediction accuracy at the block or urban scales, we are using individual building electricity use as a conservative proxy as other urban simulations have similarly done [48]. Based on the ASHRAE standard, we assess errors on the basis of metered electricity consumption in kilowatt-hours (kWh). Acceptable ranges for an energy simulation require an MBE of 10% for hourly intervals and 5% for monthly as well as a CV(RMSE) of 30% for hourly intervals and 15% for monthly. While MAPE is not commonly used to assess accuracy in energy simulation models, we include it in our analysis as it is often used for evaluating machine learning models. Additionally, different buildings might have variances in the magnitude of energy consumption, and as a result the MBE metric is susceptible to being dominated by larger buildings with higher electricity consumption. Utilizing the MAPE metric as an alternative metric allows for the normalization of errors across numerous buildings.

Overall the results shown in Table 2 demonstrate that DUE-S is able to more accurately predict electricity use as the spatial and temporal granularities increase. Compared to the ASHRAE Guidelines, DUE-S was able to more accurately predict electricity performance at the urban scale for hourly and monthly time intervals. We postulate that our model's success at these higher intervals is because aggregation reduces the variability in overall electricity consumption and creates a smoother consumption curve consistent with findings from previous sub-building [10] and residential [96] forecasting studies. Thus, by assessing electricity use on a wider spatial scale or at a larger time interval, the effects of buildings or blocks with worse individual predictions are dampened, indicating the impacts of urban context on to building energy use have been partially captured at higher spatial and temporal scales.

Fig. 6 shows the MAPE of DUE-S when predicting at the monthly interval and urban scale for the testing data. The trend indicates that the peak winter and summer months tend to perform worse than months in more temperate spring and fall seasons. One possible reason

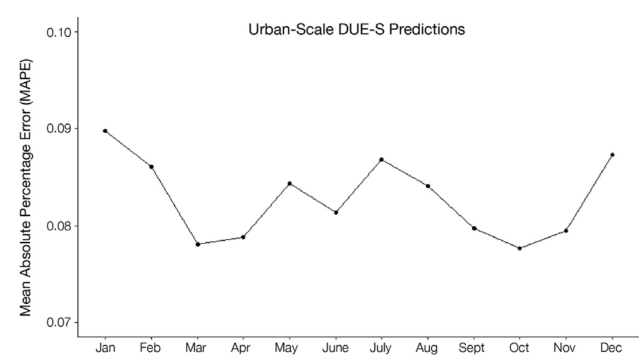

Fig. 6. DUE-S performance in estimating urban scale electricity use at the monthly interval, evaluated with MAPE.

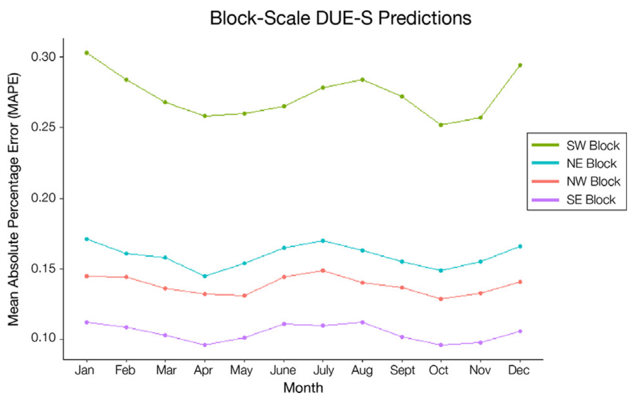

Fig. 7. DUE-S performance in estimating block scale electricity use at the monthly interval, evaluated with MAPE.

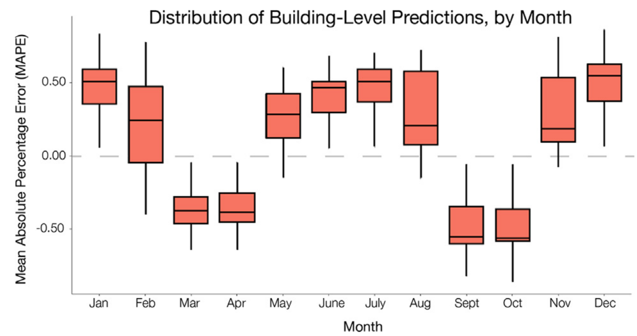

Fig. 9. Distribution of electricity use predictions by month.

is that winter and summer months are generally when university vacation periods occur, and thus the use of buildings could be irregular and unpredictable. When we dissect monthly MAPE further at the block scale (Fig. 7), we see that while each block generally follows a similar trend in seasonal prediction with urban scale simulation, there is significant variability in the performance of each block. While the southwest block is unable to estimate electricity use nearly as well as the others, it is still able to follow a similar trend in seasonality which we believe shows that the ResNet is picking up on electricity use trends across large spatial regions. However, to fully understand the drivers for why this particular block of buildings is performing much worse, we further assess the monthly MAPE at the building scale (Fig. 8). Fig. 8 indicates that some buildings, similar to the block scale, are able to predict electricity use better or worse than others. Each row represents one of the 22 total buildings in the study area, whereas each column represents a single month of electricity prediction. Darker colors in the map represent worse MAPE scores and lighter colors represent more accurate results. As indicated earlier, the southwest block, which is comprised of the upper five buildings in the heatmap, contains five buildings that are not particularly accurate in their own electricity prediction, while each of the other three blocks contains buildings that were more accurate. One possible reason is the existence of missing data, which could significantly impact the learning of interdependencies and interactions of building energy use. Some of these buildings may perform better or worse than others, and we believe that may be also because the quality of metered data we were able to collect from the university varies in its completeness. For example, one of the worst performing buildings in the northwest block has 38% of missing values, while one of the best performing buildings from the southeast has 6% missing values. In turn, by assessing which buildings perform worse than others, we can focus future efforts to collect and clean electricity data for those particular buildings.

Finally, we examine the distribution of the monthly MAPE at the building scale in Fig. 9 to show how DUE-S performs for all buildings throughout the year. Among the twelve boxplots, nine have compact interquartile ranges (IQR) but long tails, indicating that during these months at the building scale MAPE deviates from each other but otherwise generally performs well. It is clear that there are buildings with much better estimates of electricity consumption than others. When averaged, however, the final result gives a much higher error (Table 2) due to the existence of outliers. It can also be seen that the boxplots are fallen into five regions (three are above the 0.00 line and two are below), demonstrating seasonality affects whether DUE-S is under or overestimating electricity use. The spring and fall months show a trend in underestimating electricity use while winter and summer ones tend to overestimate. During the months that DUE-S tends to underestimate electricity, the variance of MAPE is smaller than other months - indicating that the model performs better when providing a conservative estimate of electricity use.

It has been demonstrated that DUE-S is capable of accurately predicting building energy use at multiple temporal and spatial scales, which could be utilized for a variety of real-world urban energy efficiency applications, such as large-scale retrofit analysis. For example, if

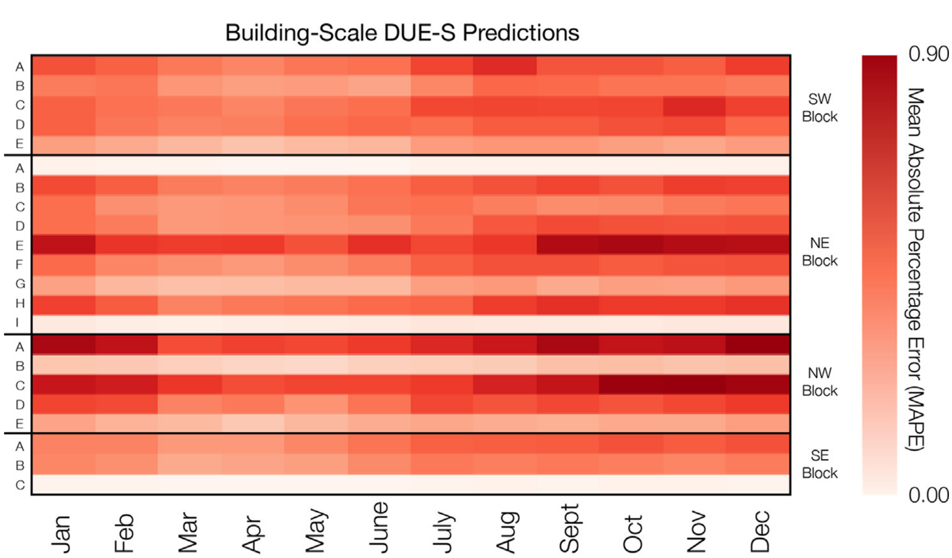

Fig. 8. Heatmap of building scale predictions at the monthly interval, evaluated with MAPE. The heatmap is divided into four sections, each comprised of buildings located at each of the four blocks.

Table 2
Summary of DUE-S results at multiple temporal and spatial scales.

	MBE (%)			CV(RMSE) (%)			MAPE (%)		
	Hourly	Daily	Monthly	Hourly	Daily	Monthly	Hourly	Daily	Monthly
Building scale	38.8	27.9	17.3	46.0	31.3	27.9	49.6	43.1	43.8
Block scale	27.1	18.2	14.7	40.6	25.1	18.5	21.4	18.3	16.9
Urban scale	10.5	7.93	4.78	25.6	14.4	11.4	12.7	9.31	8.28

an engineer was interested in understanding how changing the materiality of windows (e.g., from 6 mm Low-E glass to 12 mm Low-E glass) impacts energy use for numerous buildings in northwest block of our case study, they could utilize the DUE-S model as follows. First, they would run the DUE-S model with the baseline energy simulation to enable the residual network to learn the uncertainties associated with simplified assumptions made in the energy simulation process as well as the "hidden" urban context impacts. Next, they could take the baseline energy simulation and, holding all other input parameters constant, modify the glazing material properties of windows in the buildings receiving the potential retrofit. The resulting simulation results would show the basic energy dynamics of the proposed window retrofit. Then, the results from this retrofit simulation would become the inputs to the *same* residual network model created with the baseline energy simulation. By applying transfer learning [97] to the new input data, the pretrained network relating simulated and metered energy could also be used for the retrofit scenario. Because the only differentiation between the baseline and retrofit scenarios are the new modified window glazing inputs in the retrofit simulation, the difference in outputs from the residual network would help quantify the impact of the window retrofit on a single building in the northwest block, the rest of the block, and the ones around it.

Overall, the results of the case study underscore the value and merit of the integrated DUE-S approach, but they also demonstrate that significant amount of future work is necessary to further refine it at smaller spatial and temporal scales. Although it is common for deep learning models to use much more data than we had for this study, our ResNet was still able to pick up on the patterns presented in the available data. Furthermore, it was able to achieve results that demonstrate the potential of using deep learning to better predict energy use on multiple spatial and temporal scales by capturing some uncertainties in both modeling process and from the urban context. Besides working with a longer period of metered energy data, we believe that introducing more features to the input dataset, such as weather data or hours of operation, may help the ResNet pick up on additional patterns at the smaller spatial and temporal scales. Finally, with any data-driven model, its performance can only be as effective as the quality of its data. Because the inputs to the ResNet were the result of highly generalized energy simulations, we plan to further analyze the tradeoffs between modeling objectives and data availability to understand how the DUE-S results can be further improved. In the end, we aim to establish an integrated model that strikes the balance between extensibility and detail, as creating and maintaining comprehensive building energy simulation models for all buildings in a city is infeasible. This core objective of this paper is to propose a novel method for predicting building energy use at various spatial and temporal scales, and it represents the first key step to enable future work that explores the potential of using data-driven methods to create multiscale urban building energy models.

6. Limitations and future work

This paper aimed to take a first step in overcoming challenges faced in urban energy modeling and to test the feasibility of DUE-S: a generalized engineering urban energy simulation model integrated with a network-based machine learning model. Our goal was to understand whether an integrated model such as DUE-S could accurately characterize the energy performance of buildings at the individual building, block, and urban scale simultaneously. We evaluated our model through a case study of 22 co-located university buildings for 3 years and found that a residual neural network (ResNet) model was capable of predicting urban scale energy use on par with industry-accepted limits. However, future work is required to further validate the modeling approach on other case studies with diverse building stocks and urban morphologies to ensure the model is reliable for various scenarios. Moreover, our model was only able to successfully predict on the urban (campus) scale but demonstrated potential for achieving accuracy at other scales as well. The energy simulations relied on inputs provided by the Department of Energy's Commercial Reference Buildings and publicly available data, and specific details related to each individual building were not included in order to test the level of generalization a simulation could have to still be able to accurately predict energy use. Future work should aim to understand the level of specificity required of the energy simulations in order to improve prediction results within acceptable error ranges. Additionally, deep learning models, including ResNets, require a large number of observations in order to effectively train, develop and test their accuracy. Because one of the limitations of this study is the limited time period of provided data, we aim to train our ResNet on more observations in order to produce a model better capable of understanding the more complex patterns of building energy use. Future work also aims to analyze the performance of the ResNet in more detail by extracting the weights of each hidden layer to understand the correlations between consumption in adjacent buildings. Because the selected study area was a small cluster of university buildings, we were unable to determine its performance on a large number of densely clustered buildings of different sizes and use types. As such, we acknowledge that our case study is not fully representative of a large real city but nonetheless the results provide a high-level validation of how our proposed model would perform on a small and dense central business district (CBD) that is common in many parts of the United States. Finally, we aim to test DUE-S on a larger, more heterogeneous group of buildings in a different geographic area to further refine and improve the extensibility of the underlying framework, as well as implement DUE-S in real-world building and urban scale retrofit scenarios to support sustainable urban planning and operations.

7. Conclusion

The primary goal for this paper was to propose DUE-S: a data-driven modeling framework that integrates the computational power of a neural network model and interpretability of an engineering building energy simulation. The results of our case study analysis demonstrate the significant opportunity that exists to create more accurate multiscale urban energy models if emerging machine learning models were integrated into the current energy simulation workflow. However, in the current state, there is no generally accepted approach for urban energy modeling as there exists a significant amount of uncertainties in both buildings to be modeled and the surrounding environment. Current methods can only simulate buildings on an individual level, and fail to account for the energy dynamics and interdependencies resulting from urban context. The rapid development of new sensing technologies and smart city initiatives has led to an explosion data streams describing buildings and their urban environment, which in turn provide a significant opportunity to create more accurate multi-scale urban energy models by integrating emerging data-driven machine learning models with an engineering simulation workflow to leverage the advantages of both. Specifically, we were able to demonstrate that our integrated DUE-S model achieves acceptable level of accuracy at the urban (campus) scale as per ASHRAE standards.

Overall, an integrated engineering and data-driven approach to urban energy performance modeling can yield a model generalizable for any city or dense building portfolio data and will be able to simulate energy consumption on an individual, block, and urban scale. By visualizing the energy use of buildings across a city, policymakers will have a better awareness of the effects of new citywide interventions (e.g., implementing an incentive program for window retrofits across the city). Designers and building operators will understand the effects of energy consumption on not only their building, but surrounding ones as well (e.g., adding reflective coating to minimize glare, retrofitting the HVAC system). And finally, as data is being increasingly used in the planning of newer, smarter cities, this model can employ data from existing cities to optimize building energy use and help inform key decisions related to energy efficiency early on in the design process and as part of retrofit programming (e.g., developing planning policies related to land use and morphology, enacting a new policy to allow high-rise development). In the end, as the world rapidly urbanizes modeling the energy performance of our urban buildings will undoubtedly unlock numerous opportunities that could potentially enhance the sustainability of our cities for years to come.

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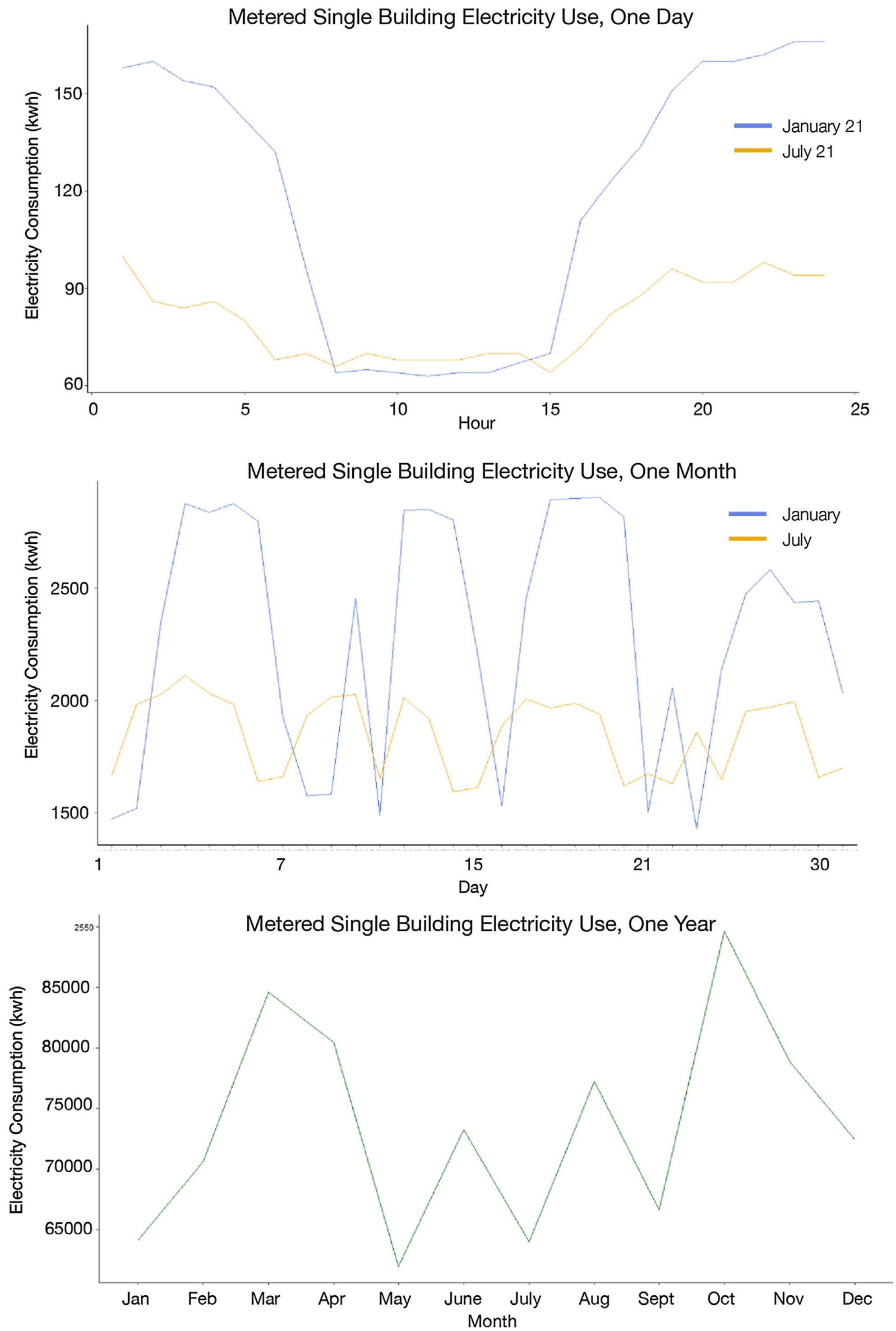
Appendix A

Electricity use profiles based on metered electricity data for a single building in the campus study area. Profiles are shown in hourly intervals for peak summer and winter days, daily intervals for summer and winter months, and monthly intervals for a full year.



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