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Ten Questions on Urban Building Energy Modeling

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Abstract

Buildings in cities consume up to 70% of all primary energy. To achieve cities' energy and climate goals, it is necessary to reduce energy use and associated greenhouse gas emissions in buildings through energy conservation and efficiency improvements. Computational tools empowered with rich urban datasets can model performance of buildings at the urban scale to provide quantitative insights for stakeholders and inform their decision making on urban energy planning, as well as building energy retrofits at scale, to achieve efficiency, sustainability, and resilience of urban buildings.

Designing and operating urban buildings as a group (from a city block to a district to an entire city) rather than as single individuals requires simulation and optimization to account for interactions among buildings and between buildings and their surrounding urban environment, and for district energy systems serving multiple buildings with diverse thermal loads across space and time. When hundreds or more buildings are involved in typical urban building energy modeling (UBEM) to estimate annual energy demand, evaluate design or retrofit options, and quantify impacts of extreme weather events or climate change, it is crucial to integrate urban datasets and UBEM tools in a seamless automatic workflow with cloud or high-performance computing for users including urban planners, designers and researchers.

This paper presents ten questions that highlight significant UBEM research and applications. The proposed answers aim to stimulate discussion and provide insights into the current and future research on UBEM, and more importantly, to inspire new and important questions from young researchers in the field.

Keywords

Building energy use; energy efficiency; urban systems; urban building energy modeling (UBEM); urban energy planning; building performance simulation

1. Introduction

Cities consume over two-thirds of the world's energy and account for more than 70% of *global* CO_2 emissions (C40.org). Based on the United Nation's prediction (un.org), the global urban population is expected to rise from 3.5 billion in 2017 to 5 billion by 2030, and energy and infrastructure choices made in the intervening years will define the difference between strong and stable urban spaces and crumbling infrastructure unable to serve our competitive needs. In the United States, more than two-thirds of the population lives in urban areas that are trying to manage growth and build for resilience in the face of more extreme weather events, while much of the aging U.S. urban infrastructure—including the buildings, transmission systems, gas pipelines, and electricity grid—need to be repaired or replaced.

Urbanization is one of the great challenges of this century, with linkages to climate change and the need to develop sustainable use of energy and other natural resources. Urban energy models aim to explore opportunities to address these issues by combining the data generated in cities with new energy simulation tools. Urban computational tools combine urban sensing, data management, and data analytics to evaluate city-scale energy and environmental systems. Urban modeling is an interdisciplinary field where computer science meets city-related fields like transportation, civil engineering, energy supply and demand analysis, environmental science, economics, ecology, and sociology in the context of urban spaces.

With buildings responsible for about one-third of global energy consumption and a quarter of carbon dioxide (CO_2) emissions, there is a huge, untapped opportunity to create and transform cities to more sustainable environments by improving building energy efficiency. More efficient buildings can generate economic benefits, reduce environmental impacts, and improve people's quality of life. Urban energy analysis is a complex, multi-scale, multi-sector challenge. Cities need to be able to evaluate their current energy use and explore how to compare, rank, contrast, and estimate strategies to reduce energy use and environmental impacts. Cities also need to evaluate building retrofit opportunities for their local stock considering the energy usage, vintage, size, type, ownership, and socioeconomic capabilities of each neighborhood. Advanced shared energy infrastructures, such as district heating and cooling systems, can achieve much higher energy efficiency by combining diverse loads, making the integrated energy use of a group of buildings less than the simple sum of the individual buildings.

Designing and operating interconnected urban systems requires dynamic computer simulation and optimization to account for the complexity of energy systems, such as different types of building systems, operating patterns, uncertainty and variability of weather, microclimate and urban heat island (UHI) effects, and occupant behavior. Recent efforts to develop decision support tools have integrated these computational urban models with geographical information systems (GIS) to obtain input data for hundreds to thousands of buildings, to model their performance and to visualize results in a format that is accessible to urban planners and designers.

Building energy modeling has been widely used to inform building energy efficient design, demonstrate code compliance, gain credits towards performance ratings, assess retrofit options, and optimize operations (Hong, Langevin and Sun, 2018). ASHRAE Standard 209 defines typical applications of building energy modeling across the building life cycle. These applications can cross over several spatial and temporal scales for various stakeholders to inform their decision making on building energy efficiency, demand flexibility, occupant comfort, and reduction of energy use and greenhouse gas (GHG) emissions.

Urban Building Energy Modeling (UBEM), described by Reinhart and Cerezo Davila (2016), is a growing field in building energy modeling, covering a spatial scale from a city block to a district to an entire city. UBEM has a strong potential to support the design and optimization of urban buildings at a large-scale for energy efficiency, sustainability, and resilience in cities. A few papers provide diverse reviews of UBEM.

Reinhart and Cerezo Davila (2016) reviewed emerging simulation methods and implementation workflows for bottom-up urban building energy models. Their review covers simulation input organization, thermal model generation and execution, and result validation. They discussed the main challenges in model calibration and results validation due to the lack of large-scale measured building energy use data. They also called for UBEMs to have stronger intellectual engagement between planners, policymakers, utility representatives, and the building modeling community in order to achieve a larger societal impact.

Sola *et al.* (2018) reviewed simulation tools to build urban-scale energy models, which include five sub-models: an urban meteorology model, a building energy demand model, a building energy supply model, a transportation energy model, and an energy optimization model. Sola et al.'s review focuses on the capacities of the simulation tools and how they work together through co-simulation. Ferrari *et al.* (2019) reviewed 17 tools targeted on an urban/district scale that can evaluate several energy services, sources, and/or technologies. These tools were classified based on their defined features: analysis type, operation spatial scale, outputs time scale, energy service, and license. Among them, six user-friendly tools were identified (energyPRO, HOMER, iHOGA, EnergyPLAN, SIREN, and WebOpt) that can provide hourly energy calculations and can be considered viable for widespread use. Ferrari, Zagarella, Caputo, and Bonomolo (2019) reviewed methods and tools for estimating hourly energy demand profiles at the district level. Frayssinet et al. (2018) conducted an overview of city energy simulation models capturing short (hourly or sub-hourly) energy dynamics and reviewed the related modeling techniques using detailed approaches. Their analysis pointed out that computational costs of such simulations are a key issue to overcome to achieve reliable microsimulation of the power demand of urban areas. Li *et al.* (2017) provided a review of the broad categories of energy models for urban buildings and describes the basic workflow of physics-based, bottom-up models and their applications in simulating urban-scale building energy use. Strengths and weaknesses of the reviewed models were presented, followed by a discussion of challenging issues associated with model preparation and calibration.

Moghadam *et al.* (2017) provided a systematic review of existing spatial urban energy planning approaches and built environment applications. Their review of UBEM focuses on modeling approaches, including both top-down and bottom-up approaches. The bottom-up approach is further categorized into building-physics or engineering models and statistical models. They summarized from the literature that the top-down approach has been considered suitable for large-scale analysis and not for the identification of the possible improvements at the building sector level at urban and regional levels; while the bottom-up approach has been recognized as suitable for urban and regional analyses.

Keirstead, Jennings, and Sivakumar (2012) proposed a theoretical definition of an urban energy system model and then evaluated the state of current practice in five key areas—technology design, building design, urban climate, systems design, and policy assessment—each with distinct and incomplete interpretations of the problem domain. They reviewed an additional field, land use and transportation modeling, which has direct relevance to the use of energy in cities. Despite their diversity, these approaches to urban energy system modeling share four common challenges: understanding model complexity, data quality and uncertainty, model integration, and policy relevance. They examined the opportunities for improving current practice in urban energy systems modeling, focusing on the potential of sensitivity analysis and cloud computing, data collection and integration techniques, and the use of activity-based modeling as an integrating framework.

Although the existing literature covers various aspects of UBEM, each has a different focus and does not address the comprehensive view of all the important aspects of an ecosystem for UBEM. They especially lack in-depth discussion of UBEM's potential applications, associated challenges, and future research opportunities. To address the literature gaps, and more importantly, to share authors' visions on UBEM, this article provides up-to-date research trends and insights for the international community, to help improve understanding of urban building energy modeling and to inform its research and application in the form of 10 questions:

- Description and importance of UBEM (Questions 1 and 2)
- Review of available UBEM tools (Question 3)
- Available urban datasets and data representation standards (Questions 4 and 5)
- Sources of local weather data for use in UBEM (Question 6)
- Methods to couple multi-physics urban system models (Question 7)
- Calibration methods of UBEM (Question 8)
- Example applications of UBEM (Question 9)
- Main challenges of UBEM (Question 10)

2. Ten Questions

2.1 Question 1: What is urban building energy modeling (UBEM)?

Urban building energy modeling refers to the computational modeling and simulation of the performance of a group of buildings in the urban context, to account for not only the dynamics of individual buildings but more importantly, the inter-building effects and urban microclimate. The goal is to provide quantitative insights (e.g., annual or seasonal energy use and demand, potential of renewable power generation) to inform urban building design and operation, as well as energy policymaking. Urban building performance metrics include near-term operational efficiency (e.g., energy use and demand at the daily, monthly, and yearly time frames), short-term demand response (e.g., electric load shedding and shifting at the minute to hour time frame), long-term sustainability (e.g., GHG emissions, impacts of climate change on energy demand at the year to decade time frame), and event-driven resilience (e.g., impact of extreme weather events such as heatwaves and wildfire on energy use, power supply, and occupant health at the day time frame). UBEM can also estimate the potential of renewable power generation from photovoltaics (PV) or wind turbine systems located on rooftops or integrated into building facades. For electric vehicle (EV) charging that uses the building power system, UBEM can integrate the EV loads into the building's overall energy demand.

Depending on user cases, UBEM can have different spatial and temporal scales. UBEM can cover spatial scales from tens of buildings in a city block to hundreds or thousands of buildings in a district, and to tens or hundreds of thousands of buildings in an entire city. UBEM typical covers temporal scales from an hour to a day, a week, a month, a year, and one or multiple decades.

Most of UBEM do not necessarily take the urban micro-climate effects into account. Usually, there is a single weather file representing either the local or entire city's meteorological conditions. Only a few models are coupled to micro-climate simulations; and even though most of them don't represent long-wave radiation exchange between buildings in a sufficient manner.

UBEM can use different modeling approaches. A top-down approach is usually data-driven, with statistical and regression models integrating building stock data, technology adoption models, and economical models to provide high-level building energy policy evaluation and scenario analysis, as well as a technology R&D roadmap. A bottom-up approach models building subsectors or down to individual buildings, using fully detailed dynamic building physics models (white box), reduced-order dynamic models (grey box), or data-driven models (black box). A detailed modeling approach usually requires a much larger amount of data to be input to the UBEM, and requires much more computing resources.

Determination of UBEM at the appropriate spatial and temporal scales, as well as modeling approaches, depends on the use cases, i.e., the questions to be answered. Other important factors to consider include availability and quality of input data, user experience with the chosen UBEM tools, and available computing resources. Users and stakeholders of UBEM include urban planners, designers, architects, engineers, energy modelers, utilities, city managers, researchers, technology vendors, governments, and policymakers.

Figure 1 illustrates the key components of a UBEM ecosystem, including datasets, simulation workflows, results, and stakeholder metrics to support decision making.

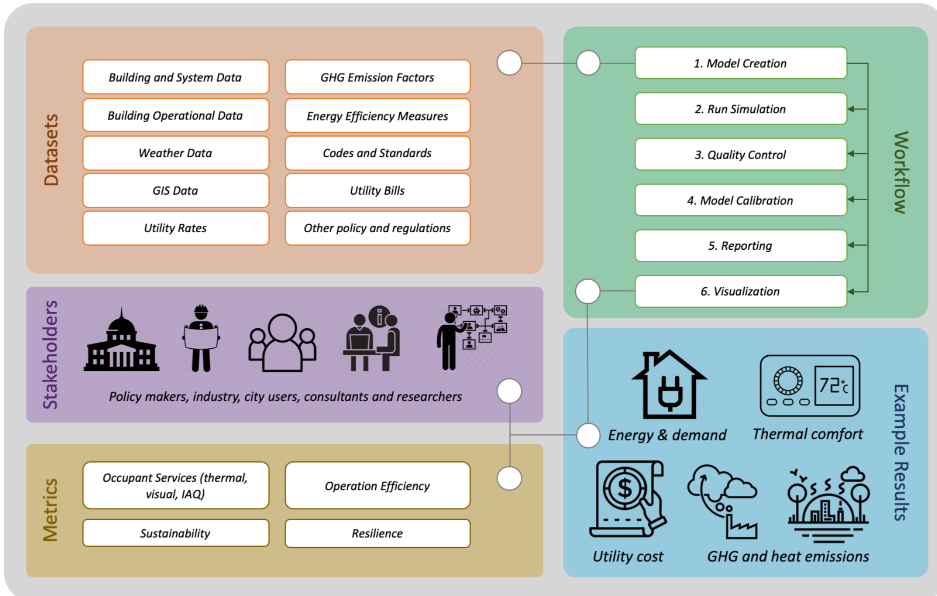


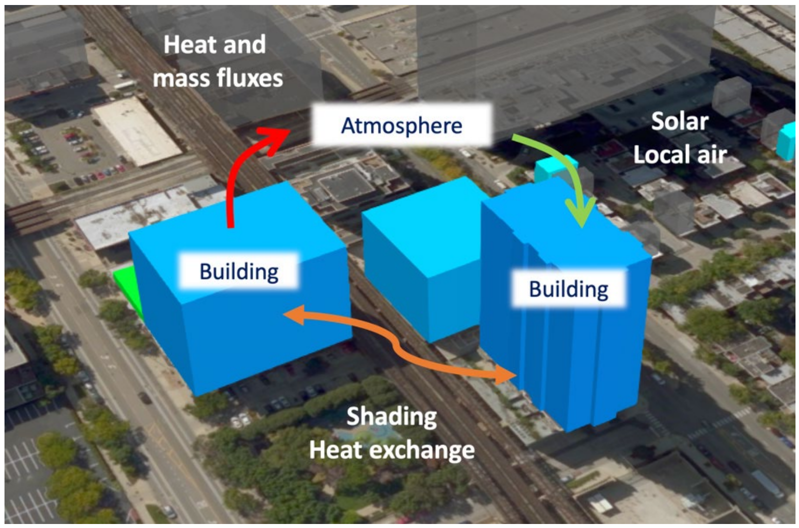
Figure 1. Overview of Urban Building Energy Modeling

2.2 Question 2: Why is urban building energy modeling needed?

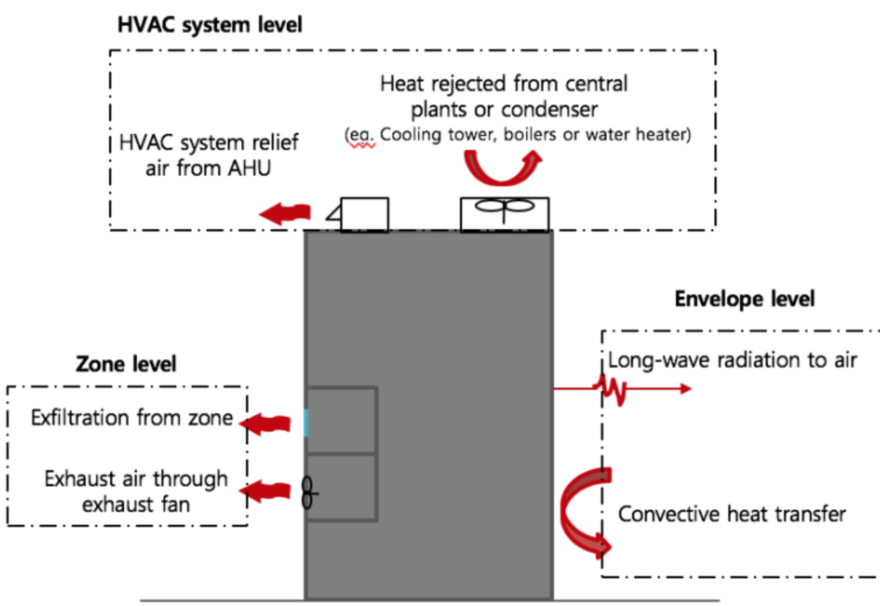
Existing methods to estimate urban building energy demand using a limited number of archetype buildings and scaling up by building floor area do not fully capture the complexity of urban buildings, especially their interconnections. The current urban energy flow modeling is mostly based on top-down building stock energy models, starting with the building energy demand for one region and successively subdividing the whole stock into smaller subsections. These top-down models provide estimates of the energy analysis if more buildings of a certain type were to be built. However, such models are limited in their predictive ability when investigating the performance of a group of buildings in an urban context. At this urban scale, bottom-up urban building energy models are expected to achieve the goals of investigating/planning the integrated energy supply-demand scenarios. Bottom-up models are based on physical descriptions and engineering calculations in and around buildings, which are used to analyze the operational energy costs and dynamic performance for the group of buildings at high spatial and temporal resolutions.

UBEM is not about scaling up energy modeling from one individual building to many buildings in a linear fashion; it is about capturing the dynamic and complex interconnection and interdependencies between urban buildings and the urban environment. Urban environment strongly influences the performance of surrounding buildings, while buildings strongly influence the urban environment. Compared with modeling buildings as solo individuals, UBEM should capture the interactions between buildings (e.g., shading, longwave radiant heat exchange, solar reflection) and between buildings and the urban microclimate (e.g., building heat release to the ambient air, local climate such as urban heat island effect influences on building performance), as illustrated in Figure 2. It should be noted that most current UBEM tools, e.g., UMI, CitySim, Teaser, and CityEnergyAnalyst, don't consider the coupling effect of heat emissions from buildings heating up the local micro-climate which further influences the building energy demand.

UBEM also simulates on-site renewable energy generation (mainly PV) and district energy systems serving a group of buildings taking advantage of their thermal load diversity. Considering urban buildings as part of urban systems (a system of systems) will enable greater performance than just considering them the simple sum of individual buildings.



(a) Shading and long-wave radiant heat exchange between exterior surfaces of buildings, and interaction of buildings with the local ambient air



(b) Heat emissions from buildings to ambient air through five mechanisms

Figure 2. Interconnections between buildings and environment in an urban context

UBEM is a powerful tool that provides simulation and analysis for urban energy planning and design, carbon emissions from buildings, and local building energy or GHG regulations and code compliance. UBEM can support users in answering a broad array of important questions about technology deployment and policy for urban buildings, such as:

- Which types of buildings have the greatest potential for energy savings and cost-effective retrofits?
- Which energy efficiency technologies can help achieve the greatest energy savings?
- Where in the city are there districts with the right mix of load density and diversity to support district energy systems, or local energy storage to reduce energy use?
- How much energy savings can be expected if all buildings in a city use a specific retrofit, such as replacing single-pane windows with double-pane windows, or fluorescent lights with light-emitting diode (LED) lights?
- If all buildings in a city upgrade to meet the current building energy code, how much energy savings and peak electricity demand reduction can be achieved?
- What is the impact of climate change on the energy use of the building stock in the next 30 or 50 years?
- What is the impact of extreme heatwaves on the energy demand of buildings with air-conditioning and on occupants' health in buildings without air-conditioning?
- How to identify buildings vulnerable to heat waves and evaluate retrofits to address the vulnerability?
- If solar PV is installed on available roofs of all buildings in a city, how much electricity can be generated? How does this meet the city's renewable energy goal? What is the cost of such a PV deployment plan? How does this change the city's building energy demand?
- What are effective technologies to mitigate the urban heat island effect? How much of UHI effect is due to the heat released from buildings? These questions can be answered through coupling of UBEM with urban microclimate simulations,

2.3 Question 3: What are the available UBEM tools?

Today's existing UBEM tools have diverse fidelity and requirements of computational resources and user inputs. Some UBEM tools are web-based (e.g., CityBES) while the majority are stand-alone applications (e.g., CitySim and UMI). Some UBEM tools use physics-based simulation engines (e.g., CityBES and UrbanOpt use EnergyPlus) while others use reduced-order models (e.g., SimStadt, CitySim, City Energy Analyst, and TASER). Most UBEM tools integrate GIS-based datasets or use CityGML-based virtual city models. More than 20 UBEM tools were selected from the literature for review and are presented with a taxonomy of the tools' spatial scale, modeling approach, data input, and application platform. Table 1 summarizes the selected UBEM tools for review.

Table 1. Urban building energy modeling tools selected for review

Approach	Tool		Developer	Calculation method	Target Users	Reference
Physics-based dynamic	CityBES	Web-based data and computing platform to evaluate energy	LBNL	EnergyPlus	Urban planners, policy makers	(Hong, Chen, Lee, *et al.*, 2016)

simualtion method		performance of city buildings				
	MIT UBEM Tool	Tool for citywide hourly energy demand load calculation	MIT	EnergyPlus	Urban planners, policy makers	(Cerezo Davila, Reinhart and Bemis, 2016)
	UMI	Urban modeling interface for energy performance analysis of neighborhoods	MIT	EnergyPlus	District energy managers	(Reinhart *et al.*, 2013)
	Virtual EPB	Automatic building energy model creation leveraging machine learning simulation using high performance computing	ORNL	EnergyPlus	Urban planners, policy makers	(Ingraham and New, 2018)
	Tool by Columbia University	Tool for community-scale energy performance analyses using calibrated building energy models	Columbia University	EnergyPlus	District energy managers	(Waite and Modi, 2014)
	Tool by Cambridge University	Tool for building energy analysis for community scale and display emission map	Cambridge University	EnergyPlus	District energy managers	(Tian *et al.*, 2015)
	UrbanOPT	Modeling tool to integrate energy loads and renewable energy at the district level to develop	NREL	EnergyPlus and OpenStudio	District energy managers	(NREL, 2018)
	COFFEE	Tool for utility customer optimization for furthering energy efficiency	NREL	EnergyPlus and OpenStudio	Utility program	(NREL, 2016b)
	CitySim	Decision support tool for urban energy planners and stakeholders to minimize energy usage and emission	EPFL	CitySim solver	Urban planners, policy makers	(Vermeulen, Kämpf and Beckers, 2013)
	SEMANCO	Semantic tools for carbon reduction in urban planning	FUNITEC	Tool specific simulation engine	Urban planners, policy makers	(FUNITEC, 2013)
Reduced-order calculation method	SimStadt	Urban energy tool for energy analysis for city districts	Hochschule für Technik Stuttgart	ISO / CEN standards based reduced-order model	Urban planners, policy makers	(Nouvel, Brassel, *et al.*, 2015)
	Energy Atlas	Spatio-semantic representation of the city structure including energy related information	Technische Universität München	ISO / CEN standards based reduced-order model	Urban planners, policy makers	(Kaden and Kolbe, 2013)
	LakeSIM	Modeling tool for infrastructure to help analyze energy efficiency of new city block development	ANL	ISO / CEN standards based reduced-order model	Urban planners, policy makers	(Bergerson *et al.*, 2015)
	Tool by Georgia Institue of Technology	A tool for building energy modeling with GIS at urban scale	Georgia Institute of Technology	ISO / CEN standards based reduced-order model	Urban planners, policy makers	(Qi Li, Steven Jige Quan, Godfried Augenbroe, Perry Pei-Ju Yang1, 2015)
	OpenIDEAS	Open-source framework for integrated district energy assessment	KU Leuven	Modelica based reduced order model	District energy managers	(Baetens, R., De Coninck, R., Jorissen, F., Picard, D., Helsen, L., Saelens, 2015)

	TEASER	Tool for multiple building energy performance evaluation	RWTH Aachen University	Modelica-based reduced order model	District energy managers	(Remmen *et al.*, 2017)
	City Energy Analyst	Computational framework for the analysis and optimization of energy systems in neighborhoods and city districts	ETH Zurich	Tool specific calculation modules	Urban planners, policy makers	(Fonseca *et al.*, 2016)
Data-driven method	UrbanFootprint	Planning tool for access to land use, policy, and resource across a range of sectors	Calthorpe Analytics	Private data-driven solution	Urban planners, policy makers	(Calthorpe Analytics, 2017)
	Tool by New York University	Web-based tool to visualize energy benchmark and predict energy performance	New York University	Data-driven regression model	Urban planners, policy makers	(Kontokosta *et al.*, 2015)
	CoBAM	Tool to estimate the adoption of energy efficient technologies for building stocks	ANL	Data-driven regression model, ISO / CEN standards based reduced-order model	Policy makers	(Zhao, Martinez-Moyano and Augenbroe, 2011)

2.3.1 UBEM tools by spatial scale

Utility scale. The Customer Optimization for Energy Efficiency (COFFEE) tool generates baseline energy models for buildings in the utility territory of the National Grid. It creates three-dimensional (3D) building models using Google imagery to determine footprints, then refines models for financial analysis, leveraging billing data and incentive data. It uses OpenStudio for model creation, Building Component Library (BCL) for retrofit measures, and EnergyPlus for a simulation engine (NREL, 2016b). Virtual EPB generates utility-scale building energy models using automatic building detection techniques from imagery data (Ingraham and New, 2018).

City scale. Several UBEM tools cover city-scale energy analysis. CityBES (Hong et al. 2016) is an open data and computing platform for urban buildings. CityBES offers building energy modeling and analysis at a city scale, with various retrofit scenarios considering a collection of 100 building technologies with performance and cost data for hundreds of thousands of buildings in U.S. cities including Boston, Chicago, Los Angeles, San Francisco, Washington D.C., San Jose, and New York City (Hong et al., 2018). Energy Atlas enables the heating demand estimation from the spatio-semantic representation of energy models of the 3D geometry of 550,000 individual buildings of Berlin, Germany (Kaden and Kolbe, 2013). UMI enables an analysis of a citywide building energy performance and retrofit strategies for 92,000 buildings in Boston (Reinhart *et al.*, 2013). LakeSim provides an urban scale building energy analysis for various policy scenarios and urban morphology for 50,000 buildings in Manhattan, New York city (Bergerson *et al.*, 2015). TEASER offers a city scale analysis and energy supply by district energy systems; a case study for about 3,000 buildings in German cities with combined heating and power plant was provided (Remmen *et al.*, 2017).

District scale. City Energy Analyst offers energy demand/supply analysis for buildings at a district scale to support decision making of energy efficiency planning (Fonseca *et al.*, 2016). OpenIDEAS is an open-source Modelica-based tool to provide solutions for optimal district energy systems

(Baetens *et al.*, 2012). SimStadt provides a quick energy modeling and simulation environment for monthly and hourly energy analysis of city districts. Urban Modeling Interface (UMI) is a Rhino-based design environment for architects and urban planners to evaluate the environmental performance of neighborhoods (Reinhart *et al.*, 2013). CitySim allows energy simulation at an urban district scale for urban form optimization and retrofit analysis (Vermeulen, Kämpf and Beckers, 2013; Emmanuel and Kämpf, 2015). Cambridge University developed a simulation framework to visualize emissions by building energy and transportation at a parcel scale, integrating data from GIS and cities' energy performance certification databases (Tian *et al.*, 2015). LakeSim helps analyze the energy efficiency planning of city blocks by leveraging GIS data and prototype buildings (Baetens *et al.*, 2012). Urban Renewable Building and Neighborhood optimization (URBANopt) is a simulation platform to capture the potential benefits of load diversity and renewable energy at the district scale (NREL, 2018).

2.3.2 Modeling Approaches

Physics-based models. Urban building energy modeling is available with different modeling fidelities. Physics-based modeling approaches capturing the full dynamic of building performance offer the highest resolution. The EnergyPlus (U.S. DOE BTO, 2019) simulation engine provides capabilities for in-depth analysis of complex building systems. EnergyPlus prototype building energy models (US DOE, 2018a) enable wide adoption of EnergyPlus for urban building stock energy research. Urban energy modeling tools such as CityBES (Hong, Chen, Lee, *et al.*, 2016), COFFEE (NREL, 2016a), UMI (Reinhart et al., 2013), Massachusets Institue of Technology (MIT) tool (Cerezo Davila, Reinhart and Bemis, 2016), and Columbia University tool (Waite and Modi, 2014) offer detailed energy performance analysis built atop of the EnergyPlus engine for dynamic energy simulation of urban buildings. Often they use OpenStudio Software Development Kit (SDK) (US DOE, 2018b) to generate energy models for EnergyPlus simulations. Another dynamic simulation engine, IDA ICE (EQUA Simulation AB, 2017), is used to replicate the energy consumption of district buildings (Signature and Approach, no date). CitySim uses its simplified simulation engine with an optimization of urban form for cooling and heating demand calculation (Vermeulen, Kämpf and Beckers, 2013), while SEMANCO uses a tool specific simulation engine to estimate energy usage (FUNITEC, 2013).

Reduced-order models. Reduced-order modeling approaches are used widely to provide a quick evaluation of urban building energy performance, requiring simple inputs aligned with normatively structured model parameter values. There are different forms of reduced-order models. Calculation standards developed by the European Committee for Standardization (CEN) and the International Organization for Standardization (ISO) (CEN, 2008) define the calculation method using a set of normative statements containing the physical building parameters and building systems for different building types. Traditionally these normative calculation methods have been used for energy performance rating in European countries (Poel, van Cruchten and Balaras, 2007; Lee, Zhao and Augenbroe, 2013). ASHRAE provides a simple thermal network model to represent heat transfer and thermal dynamics through building envelope and subsequent effect on indoor temperature (ASHRAE, 2017). The reduced-order models have modeling accuracy drawbacks, yet advantages such as computational efficiency and fewer inputs requirement, which empowered the development of UBEM tools such as SimStadt (Nouvel, Brassel, *et al.*, 2015), City Energy Analyst (Fonseca *et al.*, 2016), and an urban energy modeling application by Gerogia Institue of Technology (Qi Li, Steven Jige Quan, Godfried Augenbroe, Perry Pei-Ju Yang1, 2015). TEASER (Remmen *et al.*, 2017), OpenIDEAS (Baetens, R., De Coninck, R., Jorissen, F., Picard, D., Helsen, L., Saelens, 2015) uses Modelica libraries (Wetter and Treeck, 2018) that are based on the reduced-order calculation method.

Data-driven models. Data-driven modeling methods are applied to urban building energy prediction, which relies on real measured data, and pre-defined databases for building type, vintage, and locational data. Regression methods are used to derive inverse statistical models, which infer building design or operational parameter inputs from known outputs such as energy consumption data, locational datasets, and public records (Zhao and Magoulès, 2012; Koch, 2016). A web-based tool by New York University visualizes energy benchmark data from New York City's Property Land Use Tax Lot Output (PLUTO) database and predicts energy performance at a zipcode level using a linear regression model (Kontokosta *et al.*, 2015). The UrbanFootprint tool enables planning of energy saving scenarios for buildings at city parcels leveraging its data library of energy use, environment, land use, urban planning, and census (Calthorpe Analytics, 2017). Some of the challenges with empirically data-driven methods include: (1) training data is required for model development, (2) the model is limited to a specific location and building type, and (3) there lacks a physic explanation of certain parameters of the building performance. Commercial Building Agent-based Model (CoBAM) is a good example of a model used to reconstruct a building stock model using energy consumption survey data (Zhao, Martinez-Moyano and Augenbroe, 2011; Zhao, Lee and Augenbroe, 2015). A data-driven machine learning model that integrates physics-based energy simulation is proposed for multiple scales from a single building to the urban level (Nutkiewicz, Yang and Jain, 2017).

2.3.3 Type of input data

Data are crucial in urban scale energy modeling, and they usually come from diverse sources. Thus, integrating and processing data into a standardized data format are critical for effective interoperability among urban energy modeling applications. SimStadt (Nouvel *et al.*, 2013), Energy Atlas (Kaden and Kolbe, 2013), and TEASER (Remmen *et al.*, 2017) use the City Geography Markup Language (CityGML) (Open Geospatial Consortium, 2012) for modeling and exchange of 3D city models. GeoJSON is another standardized data format, and it is used by the URBANopt analytics platform (NREL, 2018). CityBES (Hong, Chen, Lee, *et al.*, 2016) allows the use of both the CityGML and GeoJSON data formats. The MIT tool (Cerezo Davila, Reinhart and Bemis, 2016) processes Shapefile data from city GIS data. Many other tools are governed by custom data formats that meet their tool-specific input requirements.

2.3.4 Web-based vs. Standalone desktop applications

Recent trends show that many tools leverage web interfaces to visualize energy data for benchmarking, as well as simulation results for detailed analysis of urban buildings. A web-based tool by New York University visualizes urban energy use and prediction from benchmarking data (Kontokosta *et al.*, 2015). E-City is a web platform used to provide GIS-based visualization of the whole city energy balance at the city block scale; it supports energy supply and demand balance planning (Amado *et al.*, 2018). Web-based tools create energy models of urban buildings in 3D laid over a map system. They effectively display buildings filtered by size, type, location, and building systems, and visualize simulation results using color-codes layered to building models to explain energy performance levels (Hong et al. 2016; Nouvel *et al.*, 2013; Reinhart, Timur Dogan, *et al.*, 2013; Baetens, R., De Coninck, R., Jorissen, F., Picard, D., Helsen, L., Saelens, 2015; Emmanuel and Kämpf, 2015; Cerezo Davila, Reinhart and Bemis, 2016). There are also stand-alone desktop application-based tools to load data, create and run energy calculations, and visualize the results; these tools typically use a third-party graphical interface that interacts with a calculation engine or data libraries (Reinhart *et al.*, 2013; Baetens, R., De Coninck, R., Jorissen, F., Picard, D., Helsen, L., Saelens, 2015; Emmanuel and Kämpf, 2015; Remmen *et al.*, 2017).

2.4 Question 4: What are available datasets supporting UBEM?

Development of city datasets to support UBEM is a fundamental activity (Chen *et al.*, 2019). More and more cities in the world are making their building stock data publically available at their open data portals. San Francisco's open data portal, DataSF (City of San Francisco, 2018), provides building geometry, including the GIS-based footprint and height of each building. It also includes the county's tax assessor's records and the land use dataset. The San Francisco data also includes the public building energy benchmarking ordinance data, which provides annual energy use and GHG emissions data for about 1,700 commercial buildings and 1,200 mixed residential or multifamily buildings. The building permit dataset describing changes to the buildings is also available. New York City's open data portal, NYC OpenData (City of New York, 2018), showed 314 results when searching with the "buildings" term, containing the two-dimensional (2D) building footprints as well as the 3D building models in CityGML format, the property data (building information system), and the monthly energy cost from a select portfolio of city-owned buildings. Berlin's open data portal, Berlin 3D – Download Portal (Berlin Business Location Center, 2017), provides detailed 3D geometry information of all the buildings in Berlin, including the detailed texture of each building surface. Users can select an area and download the data into 3D CityGML format with or without the textures. However, building envelope information is not available. Advanced algorithms may be developed in the future to detect the building envelope system from the surface textures. Besides the cities' open data portal, some geospatial mapping platforms also have many data related to buildings. OpenStreetMap (OpenStreetMap Community, 2018) provides open data and allows users to export the data for a selected area. The data include the 2D building footprint and a list of tags, such as building type, name, or height. Microsoft released, at Github (https://github.com/Microsoft/USBuildingFootprints), an open dataset of building footprint polygons in GeoJSON format for 125 million buildings in the United States. The Open City Model is an initiative to provide open CityGML data for all the buildings in the United States. It converted the Microsoft building footprint dataset to the CityGML format (LOD1 and LOD2) and added building height information for a limited number (about 10%) of buildings. Other private maps or real estate services providers, e.g., Google Maps and Zillow, have detailed information for buildings. However, those data are private and typically not available for UBEM. Google also established a dataset search engine (https://toolbox.google.com/datasetsearch) that can help users find relevant datasets for UBEM. Those data sources include both the building geometry (footprint, height, and number of stories) and some basic building properties (such as year of construction and use type). However, there are no detailed building information related to construction type, occupancy, HVAC systems, etc.

City-scale building datasets are crucial for UBEM. Various levels of building characteristics data are needed to enable UBEM to support energy efficiency decision making. These data include: (1) building geometry, footprint, number of stories, and total floor area; (2) year built, and change history / building permits; (3) location and climate; (4) use type and occupancy; (5) energy systems, including HVAC, lighting, internal loads, and service hot water; (6) building envelope, such as construction type, insulation for walls and roofs, and window size, location, and type; and (7) actual energy consumption data and utility bills. These data may be available for some individual buildings. Unfortunately, it is very difficult to collect those data for a large number of buildings at the city scale using the city's open public records.

Building permit records provide valuable information, such as the project year, upgraded building systems, altered building type, and so on. However, the current building permit records lack some key information needed to improve the building energy baseline model. First, the description of the records is written in the text without using standard terms. Second, the description lacks quantitative information for the renovation projects, such as the performance and capacity of the installed chillers, the properties of the new windows, and the number of replaced lighting fixtures. Additionally, many energy-sensitive renovations are not included in the building permit records, since the original purpose of building permit applications was not to monitor building energy performance improvements but to address safety and city planning.

Besides the data for each individual building, several other datasets are required for UBEM, including weather data, local building energy codes and standards, utility rates, and cost data of building technologies. The historical weather data in the typical meteorological year (TMY) format for building performance simulation are widely available for more than 2,100 cities worldwide (U.S. DOE, 2019). More and more real-time weather data become available from services like Weather Underground (The Weather Company, 2018). The local building energy codes and standards can help to provide defaults of building energy efficiency levels when the detailed system information is not available. The local utility rates and cost information of the building technologies are necessary to perform an economic analysis of energy conservation measures (ECMs) (Hong *et al.*, 2015).

2.5 Question 5: What data models and tools represent the characteristics of urban buildings?

Building data from different cities or different departments of the same city are usually represented in different formats, and no common building identifier is used to link the diverse sets of data. For San Francisco, the building GIS-based footprint data are provided in the Shapefile format, while the building characteristics are stored in multiple files with Shapefile, fixed-width text, or comma-separated values (CSV) formats. Moreover, different terms are used to represent the same data elements among different datasets. Table 2 lists some of the terms used for the same data elements in the building datasets from San Francisco, Chicago, and Portland. Moreover, the same data element in different datasets may represent slightly different things. For example, in Table 2, the building height in the San Francisco dataset is the median value of the building height; however, the building height in the Portland dataset is the average value of the building height.

Table 2. Different terms for the same data elements among different buildings datasets in three U.S. cities: San Francisco, Chicago, and Portland

Terms	San Francisco	Chicago	Portland
Building Type	LANDUSE	Property classification	BLDG_USE
Year Built	YRBUILT	year_built	YEAR_BUILT
Number of Floors	STOREYNO	Stories	NUM_STORY
Building Height	gnd1st_delta_m	N/A	AVG_HEIGHT

It is essential to gather building asset data at the city scale from a wide range of sources (e.g., surveys, city projects, city datasets, and public records) and assemble them into a single open database with standardized formats and terms. The primary data formats to support UBEM include Shapefile/FileGDB, GeoJSON, and CityGML. The ESRI Shapefile (Wikipedia, 2017) and FileGDB (GDAL, 2017) formats are popular geospatial vector data formats used by GIS software tools. They typically include 2D GIS-based building footprint information and a table of building properties. GeoJSON (GeoJSON WG, 2017) is a data format based on JSON (JavaScript Object Notation) for encoding a variety of 2D GIS data structures, which is friendly to web applications built upon JavaScript. Therefore, GeoJSON gets a lot of attention in UBEM, especially for web-based applications. However, the Shapefile/FileGDB and GeoJSON formats do not provide a schema to define the building properties, leading to inconsistency among different datasets.

CityGML is an international Open Geospatial Consortium (OGC) standard that provides an open data model to represent and exchange digital 3D models of cities and landscapes (Gröger and Plümer, 2012; OGC, 2017). CityGML enables the flexible representation of objects at various levels of detail, which is critical as data availability varies widely for a large number of buildings and other urban infrastructure. Many UBEM projects selected CityGML as the data model to represent and exchange 3D city models, especially for European research projects. CityGML was used to represent the semantic 3D city for predicting the photovoltaic potential and heating energy demand of urban districts (Eicker et al., 2014) and analyzing strategies for improving building standards (Strzalka et al., 2011). TEASER, an open framework for urban energy modeling of building stocks, includes a ready-to-use interface for CityGML (Remmen et al., 2017). OpenStudio City Database (CityDB) is a flexible framework to create and run city-scale building energy simulations with the building datasets in CityGML or GeoJSON formats (Macumber et al., 2016). CityBES accepts building stock data in both CityGML and GeoJSON formats.

CityGML defines the 3D geometry, topology, semantics, and appearance of urban objects, including buildings and their components, bodies of water, city furniture (street lighting, traffic lights), transportation infrastructure (streets, roads, bridges, tunnels), and vegetation. For many of these attributes describing 3D city models, CityGML provides its standard external code list enumerating the values for each attribute type, such as standard lists of land use type (LandUseClassType) and building usage type (BuildingUsageType). CityGML also provides various levels of details to represent urban objects for various types of applications requiring different fidelity. Figure 3 shows some examples of CityGML objects. Figure 4 shows a building can be represented at five levels of details: a simple 2D footprint; a box shape; adding sloped roofs;

adding exterior shades, windows, and doors; and full details of the interior layout and zoning. CityGML version 1.0 was released in 2008, and an extended version 2.0 was adopted in March 2012.

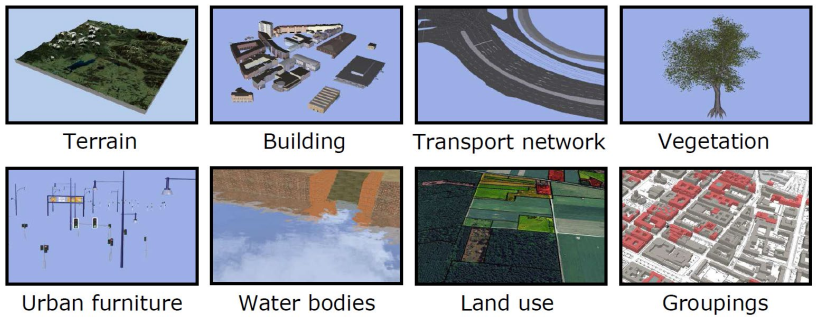


Figure 3: Examples of CityGML objects (Laurini, 2015)

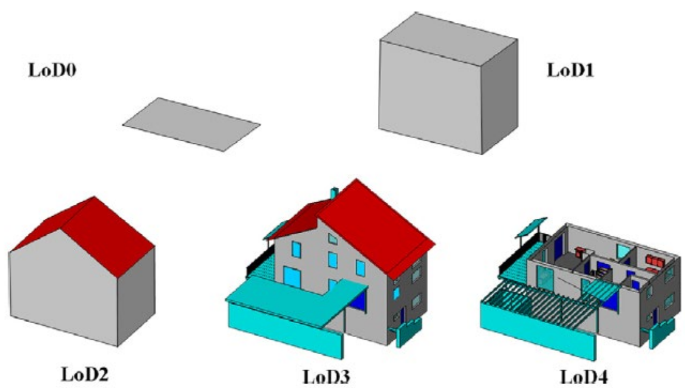


Figure 4. Five levels of details (LODs) to represent a building in CityGML (OGC, 2017)

The CityGML-based 3D city models enable information exchange and interoperability for use in city projects that need different data analytics and modeling and simulation tools, thus significantly increasing the use of such tools and reducing the time and effort needed to use them effectively. CityGML is an effective way to represent 3D geometry information. It covers several high-level building characteristics, but it does not have the detailed information necessary for building energy modeling. The Energy Application Domain Extension (ADE) for CityGML is currently under development, to integrate the building spatial and physics properties for urban energy simulation (Nouvel, Kaden, *et al.*, 2015; Benner, Geiger and Häfele, 2016). Creating an EnergyADE dataset for the building stock in San Francisco is a significant future effort, which needs detailed data from city buildings projects, e.g., energy audits or commissioning.

When representing the same amount of information for a 3D model, the size of a CityGML file is typically larger than the GeoJSON or FileGDB format. Therefore, powerful computing is necessary to process CityGML files. Splitting a city into multiple CityGML files can be more feasible.

Although CityGML provides a standardized representation of urban objects, there are a significant amount of terms that are not included in the CityGML schema but are necessary for urban building energy analysis. The Building Energy Data Exchange Specification (BEDES) (U.S. DOE and Lawrence Berkeley National Laboratory, 2017), developed by the U.S. Department of Energy (DOE) and Lawrence Berkeley National Laboratory (LBNL), is a dictionary of terms and definitions commonly used in tools and activities that help stakeholders make energy investment decisions, track building performance, and implement energy efficiency policies and programs. BEDES provides common terms and definitions for building energy data, which different tools, databases, and data formats can share. More than 50 projects, programs, and applications are involved in the development of BEDES.

2.6 Question 6: How can local weather data be generated and used for UBEM?

Integration of urban climate effects in UBEM is becoming essential to achieve a more accurate assessment of building energy consumption in urban areas. Many previous studies have documented significant impacts of the urban microclimate on the thermal loads, and thus building energy performance (Dorer *et al.*, 2013a; Hong, Chang and Lin, 2013; Savić, Selakov and Milošević, 2014; Bourikas, 2016; Pisello, 2017). For instance, the effects of UHI, a term raised by Manley in 1958 (Manley, 1958), might lead to changes to building energy demand (e.g., a decrease in heating but an increase in cooling) depending on the city (Davies, Steadman and Oreszczyn, 2008), type of building (van Hooff *et al.*, 2016), or meteorological conditions (Xu *et al.*, 2012), which yield a wide range of impacts on energy consumption and occupant health. A recent modeling study based on a building located in the center of Rome, Italy, indicated that the energy consumption of cooling would be underestimated by 35%–50% if the climatic effect of the heat island is not considered (Ciancio *et al.*, 2018). More studies related to the urban microclimate and the UHI effect and its mitigation technology solutions can be tracked down in a recent special issue of *Urban Science* (Yang and Santamouris, 2018).

During the past decades, urban microclimate studies have ranged from measuring urban-rural temperature differences to physical modeling of urban microclimate process variables, expanding from a scaled physical model to a realistic urban microclimate model (Alexander and Mills, 2014). A wide range of approaches has been employed to explore the urban microclimate and to generate local weather data. In general, these approaches can be categorized into two types (Mirzaei, 2015): (a) observational approaches and (b) simulation approaches. The observational approaches refer to measurement techniques and the theoretical physical models (such as thermal remote sensing techniques and atmosphere boundary layer research), while the numerical simulation approaches, including computational fluid dynamics (CFD) and other weather data generator tools, are strongly advocated by the rapidly developed computing communities, which are also supported and validated by the measured results. Conversely, the simulation approaches are used to conduct comparative analysis of all relevant flow variables at different scenarios within finer scales, which are more adequate for further integration with UBEM.

From the UBEM perspective, the knowledge of the local weather data (e.g., temperature, pressure, wind speed, solar radiation, etc.) will present as the boundary conditions of the urban environment, which is the key input parameter for the building energy modeling. However, the weather data employed in traditional UBEM is often obtained from either measurement at remote open areas (e.g., airports near large cities) or historical datasets (approximately during the past 30 years), which is usually compiled as a TMY weather file. These weather data often fail to present the actual microclimate or boundary conditions of the local city, and are thus prone to produce erroneous results for the studies on specific blocks and districts (Mylona, 2012). Therefore, obtaining high-resolution weather information around the targeted urban buildings will lead to more accurate UBEM results.

Currently, with the recent mass production of affordable and user-friendly weather stations, as well as the increasing technology of automated measurements and data analysis, a hyper-local weather forecasting approach is booming. Websites such as Weather Underground, Dark Sky, and Weather Observations provide hubs for sharing weather data from local weather stations, enabling different groups of users to access hyper-local, real-time weather observations and forecasts. Other weather APIs (Application Programming Interface) such as Cal-Adapt and Open Weather Map also provide a wealth of data and information for developers and researchers to access, and based on that information they can easily build their domain-specific visualization and planning tools on top, considering their own research or design purpose.

On the other hand, driven by the increased necessity of higher resolution and detailed boundary information, as well as the recent advances in computing infrastructure, CFD is still quite a popular tool for simulating and predicting the urban microclimate (e.g., OpenFOAM and Nek5000). Many recent studies coupled CFD and UBEM simulations to predict and analyze urban energy and urban infrastructural systems. A recent work by Katal et al. ((2019) integrated a CFD tool named CityFFD with CityBEM to model and evaluate the building resilience under the extreme weather. Another recent work by Lu et al. (2019) developed a coupled modeling framework for energy-transportation-communication infrastructure in smart and connected communities. Urban-/building-related simulations are conducted at different spatial scales. These range from the meteorological mesoscale (i.e., atmospheric events at the city scale, Sasaki, 2008) over the meteorological microscale (i.e., the relevant flow variables around building groups, Mochida and Lun, 2008) to the building scale (i.e., the boundary information for modeling the energy consumption for the specific building, Allegrini *et al.*, 2015) and the indoor environment (i.e., the indoor environment modeling and building services engineering, Hong, Chou and Bong, 2000). The target parameters include the outdoor temperature, relative humidity, heat flux, solar radiation, wind velocity, turbulent kinetic energy, pollutant concentration, and air quality index.

Most of these previous studies employed the Reynolds-averaged Navier-Stokes (RANS) and Large Eddy Simulations (LES) to solve the governing equations, where specific turbulence models/sub-grid scale models were used and improved. A recent review article written by (Toparlar *et al.*, 2017) investigated the previous 183 studies on the CFD analysis of urban microclimate. It emphasized the advantages of CFD simulations both in obtaining the explicit coupling of different variables as the boundary information for further UBEM, and also in resolving the flow field at a finer scale (e.g., urban, building—even human—scale). However, despite the benefits of CFD, the balance between high-resolution results and reducing computational power and time always has posed a challenge to its widespread, successful application in UBEM. Thus, the improvement of simpler models remains one of the largest challenge in this area (Kanda *et al.*, 2007). In addition, CFD requires a high-resolution representation of the urban geometry (Mirzaei and Haghighat, 2010), and the sub-grid implications for turbulence models also require consistency with the correct physical interpretation (Schlünzen *et al.*, 2010).

A more common approach is to use the comprehensive tools that couple the data analytics science with the numerical predictive models to generate the near-surface urban climatic information. Tools such as Urban Weather Generator (UWG) and Weather Shift morph rural weather data and historical high frequency weather data, respectively, to present the future urban weather data by setting a series of location-specific morphological parameters (e.g., building material thermal properties, building surface fraction) and future-periods emission scenarios (e.g., RCP scenarios). UWG calculates the hourly values of urban air temperature and humidity inside the urban canyons, given the meteorological measured information and the reciprocal interactions between the building and the urban climate, which will be later used to account for the UHI effect in UBEM (Bueno *et al.*, 2013).

The Weather Research and Forecasting (WRF) model, which is one of the most commonly applied weather forecasting tools in the climate science community, is capable of capturing atmospheric motions on scales ranging from continent to near building scale (Chen *et al.*, 2011; Powers *et al.*, 2017). This simulation first interpolates the meteorological and actual measured data into the model domain as a pre-processing stage, and then calculates the weather conditions under a finer spatial and temporal scale by using the rich suite of physics packages such as microphysics, radiations, and planetary boundary layer parameterization. A recent work by (Jain *et al.*, 2018) presented a coupling methodology and results of one-way coupling where WRF provided local weather data to the EnergyPlus building energy model for a test area within the city of Chicago, which emphasized the effect of urban microclimate boundary conditions on energy use prediction. Compared to the aforementioned UWG and Weather Shift tools, WRF uses a more complex model which is computationally intensive.

Another tool, the Urban Multi-scale Environmental Predictor (UMEP), was developed as a plugin for Quantum GIS (QGIS), and is also an integrated tool for generating weather data to be further applied in evaluating urban energy consumption (Lindberg *et al.*, 2018). An important capability of UMEP is to couple relevant processes by using common datasets across a range of applications. There are also other tools that have been widely applied in generating the local weather data and could be integrated with UBEM, such as Parallelized Large-Eddy Simulation Model (PALM)—used to model the atmospheric turbulence and varieties of boundary layers (e.g., urban canopy flows, cloudy boundary layers) based on the non-parallelized LES code (Maronga *et al.*, 2015) and ENVI-Met—a 3D microclimate model capable of simulating the turbulent flow around the buildings and heat exchange process at urban surfaces, using the observed/existing weather data as the meteorological boundary conditions (Yang *et al.*, 2012).

In summary, for UBEM, it is recommended to use the local weather data: either the preferred measured weather data or the calibrated simulated weather data.

2.7 Question 7: How can results from UBEM be calibrated?

Due to the limited publically available information of individual buildings in cities, lots of default data and many assumptions must be made to conduct detailed energy modeling. Therefore, there are inherent uncertainties with UBEM results. Calibrating the urban building energy models is usually based on annual (rather than monthly or hourly) energy use data of individual buildings.

The model calibration is commonly defined as an inverse approximation because of the need to tune necessary inputs to reconcile the outputs by a simulation program as closely as possible to the measured energy data (Yang and Becerik-Gerber, 2015). There are well-demonstrated manual or automated model calibration methods for individual buildings. The manual model calibration methods are not suitable for UBEM. There are several automated calibration methods developed to calibrate individual buildings, including optimization-based methods (O'Neill and Eisenhower, 2013; Yang *et al.*, 2016), pattern-based methods (Sun *et al.*, 2016), and Bayesian calibration methods (Chong *et al.*, 2017; Lim and Zhai, 2017). Although those automated calibration methods can be directly applied to calibrate UBEM, the number of simulations required to calibrate the UBEM is proportional to the number of buildings. For example, if it takes 100 simulations to calibrate one building, it may require 100,000 simulations to calibrate 1,000 buildings. However, the buildings in the UBEM share lots of information. They are typically located in the same city with the same or similar climate conditions (weather files). They are restricted or guided by the same standards and laws, and may have very similar features. They have same default assumptions for the archetype. If many simulations were run to calibrate some buildings in the UBEM, those simulation results may be used to speed up the calibration of other buildings. The UBEM calibration should not be a simple scale-up of the methods used for individual buildings.

There are limited studies about UBEM calibration. Sokol et al. (Sokol, Cerezo Davila and Reinhart, 2017) presented a method to define unknown or uncertain parameters in an archetype as probability distributions and use measured energy data to calibrate those distributions by Bayesian calibration. Six high-uncertainty variables with three to five values were chosen to run more than 1,000 simulations per building for creating a coarse parametric grid. A meta-modeling procedure was developed to create polynomial regression models for every building based on the coarse grid parametric results from EnergyPlus. The meta-models were used for the Bayesian calibration to determine the distribution of those high-uncertainty parameters. Results showed that both annual and monthly Bayesian calibration lead to significantly better annual energy use intensity fits compared to traditional deterministic archetype definitions. However, this method was based on the calibration of each building, which requires more than 1,000 simulations to train the meta-models for each building. Nagpal et al. (Nagpal *et al.*, 2019) employed statistical surrogate models with an optimization algorithm to estimate properties of unknown building parameters. Up to 28 unknown parameters with three values each were selected. A surrogate model was developed using Random Forests and Neural Networks based on 200 to 400 training samples. The surrogate model-based calibration method required 200 to 400 simulations to train the surrogate model for each building.

Occupant behavior can significantly influence simulation results not only for individual buildings but also a group of buildings in an urban district. An et al. (2018)developed detailed occupant behavior models and simulation approaches to consider diversity of occupant activities in a residential district to demonstrate the improvements in the simulated peak demand and energy use compared to the traditional homogeneous (same occupant assumptions for each individual building) assumptions of occupant activities.

More research is needed to consider all the buildings in UBEM as a connected network, to speed up the model calibration for UBEM.

2.8 Question 8: What are methods and tools for coupling UBEM with other urban systems models?

Sustainable urban development involves a wide range of integrated urban systems in network structures. Understanding the city as a cross-departmental integrated system enables planners to address critical issues in urban development, such as energy resiliency in a climate change, demand response, innovative mobility, reducing urban sprawl, and efficient management of urban services. It is an important step to represent and simulate the interrelationships between urban systems at an urban scale, which includes the interaction between building energy models, urban climate and microclimate models, transportation models, and socioeconomic models (Tsai and Ghazal, 2017). Co-simulation between models is necessary to understand the impact of systems interacting with each other in real time. We reviewed the methods and tools to facilitate the co-simulation of building energy models and other components in the integrated urban system, including (1) the urban atmosphere, (2) urban transportation and mobility, and (3) district-scale energy systems. Figure 5 illustrates their interactions.

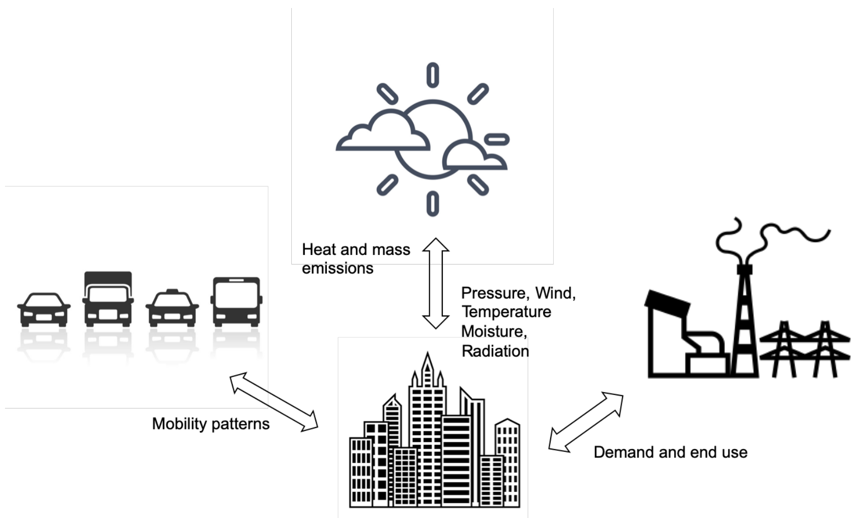


Figure 5 Buildings' interactions with other urban systems (transportation, urban climate, and grid)

Urban climate and microclimate can strongly influence building energy use (Pisello *et al.*, 2015). The various effects include (1) local air temperature and humidity, (2) local air movement, and (3) solar irradiation and specular and diffuse reflections (Dorer *et al.*, 2013b). On the other hand, buildings also influence the boundary conditions of urban canopy models as (1) buildings' geometry and layout has thermal effects on the heat and airflow (Sharmin, Steemers and Matzarakis, 2017), (2) exterior surfaces of buildings exchange heat with the urban environment through sensible heat convection and radiation simulations (Hong and Luo, 2018), and (3) buildings release heat and moisture through cooling towers, condensing units, and exhaust air to the urban environment. Figure 6 illustrates the coupling schema between buildings and urban atmosphere models via urban boundary conditions, as well as via mass and heat flow exchange. Consideration of the two-way impact between buildings and the urban atmosphere is essential to conducting a proper assessment of urban energy and environment performance in urban areas.

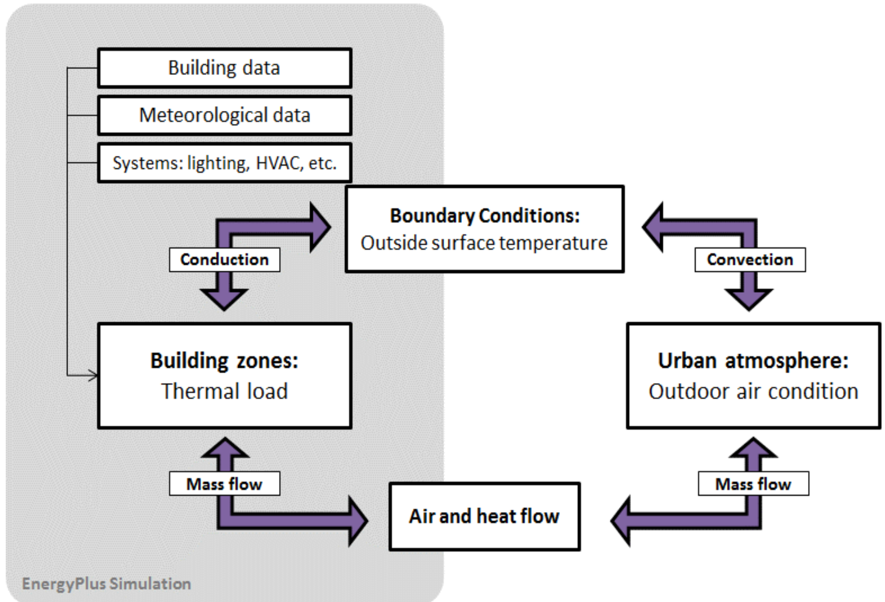


Figure 6. Coupling schema between building energy models and urban atmosphere models

An approximate approach of one-way coupling has been used to evaluate the direct impact of the environment on buildings (Malys, Musy and Inard, 2015; Pisello *et al.*, 2015; Palme *et al.*, 2017). For example, Gobakis and Kolokotsa presented the one-way coupling of the ENVI-met (Huttner, Bruse and Dostal, 2009) microclimatic environment simulation tool and the building energy simulation program ESP-r to achieve a better energy simulation of the building (Gobakis and Kolokotsa, 2017). Yang et al. also presented a quantitative analysis of building energy performance linking ENVI-met to EnergyPlus (Yang *et al.*, 2012). ENVI-met, in these two studies, calculates dynamically the convection heat transfer coefficient between the outside environment and the building outside walls to feed the building energy models. On the other hand, numerical simulations of atmosphere modules were conducted to study the one-way thermal effects of buildings on local atmospheric flow (Salamanca and Martilli, 2010; Yang *et al.*, 2012; Lin *et al.*, 2016), and they concluded that the local microclimate is sensitive to changes in the physical parameters of the urban surfaces, such as wall surface albedo (Gros, Bozonnet and Inard, 2014).

Several studies also have presented different methods to conduct two-way coupling of building energy and urban atmosphere models, to evaluate their interactions. The difficulty of this set-up lies in the scale compatibility, as it requires an accurate and high-fidelity thermal model to represent the psychical status and interactions of buildings and their environment. Two approaches are commonly used in simulating the two-way coupled system. One is to combine both physical components and processes into the one model hierarchy. For example, the SOLENE-microclimate model was developed to model urban microclimate and building thermal behavior as an integrated thermo-radiative model, considering the interactive effects among atmosphere, building wall or roof, green surface, and indoor air (Malys, Musy and Inard, 2015; Musy et al., 2015; Gros et al., 2016). However, due to the complexity of coupled physical processes, the approach can be difficult to scale in large urban areas. Another widely used approach is to use co-simulation frameworks, such as Functional Mockup Interface (FMI), for data exchange in run-time between models. Thomas et al. (2014) developed an EnergyPlus and CitySim coupling architecture, extending the urban canopy model solver in CitySim to use the FMI standard for co-simulation to exchange simulation variables with the EnergyPlus model at each time step. Miller et al. (2015) applied a similar methodology to consider the long wave exchange as part of a co-simulation process to exchange various weather, load, and environmental information between CitySim and EnergyPlus. Yang et al. (2012) developed an architecture coupling the urban microclimate model ENVI-met and EnergyPlus, exchanging surface boundary conditions using the Building Controls Virtual Test Bed (BCTVB) co-simulation platform. For buildings and their environment co-simulation, land use and building geometry data are used to initialize both building and urban canopy models. Katal et al. (Katal, Mortezazadeh and Wang, 2019) introduced CityFFD (City Fast Fluid Dynamics), an urban-scale fast fluid dynamics model for microclimate modeling to couple with CityBEM (City Building Energy Model), an urban building energy model with archetype buildings for aerodynamics and heat transfer information exchange at run time to produce high-resolution results of building thermal load, microclimate condition, and building behavior during extreme weather. However, limited data resources in past studies allowed co-simulation to be performed only at a limited level of detail.

Integrated planning also involves considering urban building energy efficiency along with urban morphology and urban mobility. Metropolitan planners are facing increasingly complex issues in modeling interactions between the built environment and multimodal transportation systems (Tsai and Ghazal, 2017). Some pioneering research has demonstrated the potential for gaining the ability to model urban systems across simulated land use, travel demands, traffic flow, and building energy consumption, to understand district power consumption and pollutant emissions. Both simulation and data-driven methods are applied to understand the urban human mobility, in order to provide representative occupancy data for UBEM studies. For example, Shirgaokar et al. (2013) conducted an integrated study in Jinan, China, analyzing the district's environmental performance using building energy evaluation and traffic microsimulation models. Results showed that an integrated optimized design would reduce energy loads by over 25% compared to business as usual (Shirgaokar, Deakin and Duduta, 2013). Another research by Berres et al. (Anne Berres, Piljae Im, Kuldeep Kurte, Melissa Allen-Dumas, 2019) introduced an urban scale mobility model, set up with the transportation model, TRansportation ANalysis SIMulation System (TRANSIMS), to estimate building occupancy for UBEM in a sample community in Chicago. However, for both studies, the methodology was based on running a combination of different scenarios across different models. With a data-driven approach, Marins and Roméro also presented a study of building energy modeling on the scale of urban districts and neighborhoods, envisioning land use and urban circulation, as well as energy efficiency of urban areas (Marins and Roméro, 2014). Mohammadi and Taylor (2017) also conducted a spatial regression analysis of positional records containing human mobility and energy consumption data in Greater London and the City of Chicago in residential and commercial buildings over the course of one month revealed spatial dependencies for buildings' energy consumption on human mobility. Based on the analysis, they presented an urban-level spatiotemporal approach for predicting buildings' energy demand using individual positional records, introducing a multivariate autoregressive model in reduced principle component analysis (Mohammadi and Taylor, 2017). These studies conclude that urban building energy use simulation should consider the effects of residents' location-based activities that influence patterns in energy supply and demand. Further, to understand the interactive effects of urban building energy consumption and mobility, especially considering interconnected factors such as occupant flow and electrical vehicle charging, more-detailed data communication and coupling architecture still requires investigation.

Simulating and optimizing district energy systems also requires co-simulation with dynamic building models, as the real-time predicted loads and indoor environment variables of urban buildings are important for control decisions in a district system. The process involves long-term simulations of a large number of buildings, including internal energy supply or energy conversion systems, in combination with external energy supply systems like the electrical grid. Several co-simulation architectures have undergone development in the past few years, such as MESCOS (Molitor *et al.*, 2014), MOSAIK, and Modelica libraries (Bu¨nning *et al.*, 2017; Schweiger *et al.*, 2017; Zarin Pass, Wetter and Piette, 2018). MESCOS is a platform that supports the design of control and energy management algorithms for city district scale energy systems. Embedded in the platform, the building energy simulators exchange load prediction and control signals with the district system, interfaced and coupled through a runtime infrastructure (RTI), taking care of the time management and the data distribution management. The MOSAIK framework also proposes an RTI that allows for automatically composing simulation scenarios randomly or following defined patterns for the simulation of active components in the smart grids. Under the scope of IEA Annex 60 on "New generation computational tools for building and community energy systems based on Modelica and Functional Mockup Interface standards," several libraries are under development using the Modelica co-simulation platform, coupling district-level plant models with building energy demand simulation using EnergyPlus.

Distributed energy resources simulation tools, such as DER-CAM (Stadler et al. 2014), in principle, can adopt similar coupling approaches for co-simulation with UBEM to evaluate renewable energy technologies and optimize controls for microgrid.

Overall, for UBEM, it is important to consider the buildings' interconnections and dynamic interactions with other components in the urban system, and past research has illustrated the gaps between modeling an individual urban component alone and implementing co-simulation across various urban systems. In general, the key challenges lie in achieving consistency of data and model, and resolving the data synchronization of models with a different temporal and spatial resolution (Wetter, 2011; Wang, Siebers and Robinson, 2017), as different simulation layers of a coupled urban system can be executed in parallel or in series. Beyond that, in most cases, the computational cost is high with high-fidelity model representations and coupling resolutions. To represent the data interoperability and system interdependency in heterogeneous infrastructures, recent research has demonstrated proof-of-concept multi-level, multi-layer, multi-agent framework to enable flexible modeling of the interconnected energy, transportation, and communication systems (Lu *et al.*, 2019b). Overall, it is crucial to design an efficient data storage and communication hub architecture to coordinate the model coupling and choose an appropriate execution model for each individual subsystem.

2.9 Question 9: What are the example applications of UBEM?

The stakeholders of UBEM applications involved in the development or operation of livable, healthy, economically profitable, and energy efficient cities and communities are diverse; hold different needs; and play miscellaneous roles in the urban systems. Stakeholders of UBEM can be grouped into five categories, including: (1) decision makers (urban policymakers and city program managers), (2) industry (investors, technology vendors, urban developers, utilities), (3) city users (residents, local communities, visitors), (4) urban energy planners and consultants, and (5) urban researchers.

Aligned with the stakeholders' interest, potential applications of UBEM are reviewed in three domains as summarized in Table 3.

Table 3 Example applications of UBEM

Domain of applications	Objectives	Reference
End use energy auditing and benchmarking	Energy savings	(Gaube and Remesch, 2015; Srebric, Heidarinejad and Liu, 2015; Heidarinejad *et al.*, 2017; Brøgger and Wittchen, 2018; Caro-Martínez and Sendra, 2018)
	Development of codes and standards	(Abdolhosseini Qomi *et al.*, 2016; Hong, Chen, Piette, *et al.*, 2016)
Demand energy auditing and forecasting	Demand flexibility	(Pezzulli *et al.*, 2006; Fu *et al.*, 2009; Delmastro *et al.*, 2017; Mohammadi and Taylor, 2017; Wang *et al.*, 2018)
	Urban resiliency	(Gros, Bozonnet and Inard, 2014; Link, Pillich and Klein, 2014; Caro-Martínez and Sendra, 2018; Frayssinet *et al.*, 2018; Oregi *et al.*, 2018)
Existing urban buildings retrofiting	Energy savings; GHG emissions reduction; Cost effectiveness	(Ward and Choudhary, 2014; Lee *et al.*, 2015; McArthur and Jofeh, 2016; Monteiro *et al.*, 2018; Nagpal and Reinhart, 2018)
Urban energy planning	Energy efficiency	(Chow, Chan and Song, 2004; Fu *et al.*, 2009; Lin *et al.*, 2010; Koch, 2016; Delmastro *et al.*, 2017)
	Urban resiliency under climate change effects	(Pisello *et al.*, 2015; Martin *et al.*, 2017; Ciancio *et al.*, 2018; Katal, Mortezazadeh and Wang, 2019)

First of all, the formulation of energy policies for urban building stock frequently requires the evaluation of the overall building energy performance of the urban districts (Tardioli *et al.*, 2018).

UBEM has significant potential to inform decision makers of how much energy could be saved if appropriate actions are enacted. Moreover, to study the distribution and determinants of energy use in large buildings, peer-to-peer comparisons by energy benchmarking encourages transparency in energy efficiency markets (Pérez-Lombard *et al.*, 2009) and predictive models of building energy use at the district and city scales help capture more generalized energy consumptions behaviors (Kontokosta and Tull, 2017). Besides, UBEM also provides knowledge for policymakers to develop industry standards (e.g., better design of tax rebates and energy incentives), as well as to provide technical assistance as needed.

Second, UBEM offers a common approach to district planning and retrofitting by evaluating and prioritizing different system design options and energy conservation measures (ECMs) for the cities-scale analysis. In general, UBEM helps users understand the overall potential costs and benefits of retrofitting a large portfolio of diverse-use buildings in terms of reducing global GHG emissions associated with building energy use. For example, Wang et al. presented the building stock model CESAR (Combined Energy Simulation and Retrofitting), which employs EnergyPlus as its simulation engine to perform the assessment of different future building stock transformation scenarios and an analysis of the energy demand and emission reductions potentials (Wang *et al.*, 2018). For existing districts, by applying the UBEM tool – CityBES, Hong et al. (2018) also presented a retrofit analysis case study to evaluate the energy saving potential and cost effectiveness of individual ECMs, as well as ECM packages for small and medium office and retail buildings in San Francisco (Chen, Hong and Piette, 2017). These studies have demonstrated the feasibility of UBEM to serve as a facility planning and maintenance tool for the assessment of effective strategies to reduce energy footprints and GHG emissions (Abdolhosseini Qomi *et al.*, 2016), as well as the potential to evolve over time as new information becomes available (Buffat *et al.*, 2017). On the other hand, the studies also point out that future efforts are required to calibrate district- to city-scale building energy models and validate the results (Booth, Choudhary and Spiegelhalter, 2012; Louis and Cerezo Davila, 2016; Santos *et al.*, 2018).

In addition, the rapid development and growth of urban areas has caused significant impacts on the built environment, such as the UHI effect (Santos *et al.*, 2018) and extreme heatwaves exacerbated by the UHI effect. UBEM was applied to perform a detailed analysis of how these phenomena can have major impacts on city energy use and how energy fluxes may result in changes of the microclimate and contribute to climate change due to the increased heat (Zheng and Weng, 2018) and GHG (Akbari *et al.*, 2016). For example, Santosa et al. evaluated the impact of the urban context to energy consumption and UHI in a representative district in downtown Abu Dhabi (UAE) via urban-scale modeling and calibration using metered building energy consumption (Santos *et al.*, 2018). Detailed UBEM provides insights on the developments of climate change and urban heat island mitigation techniques, such as highly reflective materials, cool and green roofs, and cool pavements (Gros, Bozonnet and Inard, 2014). These studies reveal the need for higher-fidelity simulations and coupled calculations for more accurate building energy modeling in urban environments.

Last but not least, there are also critical needs for urban energy supply designers to estimate the energy demand and flexibility of buildings at a district or city scale. Reliable microsimulation of power demand of urban areas remains a major research issue (Frayssinet *et al.*, 2018). Integrated modeling systems can serve to evaluate and improve the energy performance of urban energy systems' design and operation in a variety of perspectives (Wang, Siebers and Robinson, 2017), including maximizing energy conservation, grid-efficient building stock planning and control, renewable energy generation and distribution, and large-scale energy storage. In particular, research has demonstrated the need for dynamic UBEM in city district energy system design and optimization, as a dynamic representation of building systems imposes constraints on the possible control algorithm (Molitor *et al.*, 2014).

2.10 Question 10: What are the main challenges in UBEM?

Although UBEM emerges as a field with significant and growing interest (based on papers and presentations at the 2017 and 2019 IBPSA Building Simulation conferences and ASHRAE conferences since 2014), UBEM is facing challenges, including but not limited to:

- **Interconnected urban systems**. Studying interdependencies of urban systems is necessary. This requires coupling and co-simulating multi-physics urban system models including buildings, district energy systems, urban microclimate, transportation, and electric grid, at varying spatial and temporal resolutions. Data exchange mechanisms, coupling methods, and synchronization control of simulating several interconnected urban system models remains a technical challenge.
- **Big data**. UBEM requires a large amount of data. It takes significant effort to collect and integrate the datasets into a standardized format for interoperability. Data models and standards are still needed to streamline representation of metadata, and a vast amount of urban datasets are needed to enable more adoption of UBEM. Data quality, privacy, access, and security are issues that still need to be addressed. Detailed building characteristics and actual energy use data are especially needed for UBEM.
- **Workflow**. A seamless workflow of UBEM enabled by an open data and computing platform is needed to perform large-scale urban building analyses. Such a platform should also have 3D GIS-integrated visualization capability to display and provide actionable insights from a large number of UBEM results, which will support stakeholder decision making.
- **Computing resources**. Simulating all buildings in a city requires significant computing resources. For example, modeling annual energy performance of one million buildings in the City of New York in a reasonable amount of wall clock time (say a few hours) can be an exascale computing problem that requires next-generation supercomputers.
- **Collaboration**. Various groups of UBEM researchers and consultants developed different UBEM tools, datasets, and use cases lacking standardization, interoperability, or collaboration, and making it difficult to reuse data and tools or to compare and validate results from UBEM tools. Collaborations between the UBEM developers, researchers, stakeholders, and urban policymakers are strongly encouraged, to accelerate the adoption of UBEM and ensure a high societal impact that supports cities' goals of efficiency, suitability, and resilience.

3. Summary and Future Perspectives

Urban building energy modeling is a powerful tool to inform urban building energy planning and retrofits, as well as building-grid integration. The increasing research, development, and applications of UBEM are made possible due to: (1) more practical use cases and values for stakeholders, (2) more affordable cloud computing or high-performance computing, and (3) big data made available from diverse sources and low-cost sensing and metering at scale. Smart cities are deploying technologies of urban sensing. Data streams from smart city projects and infrastructures provide good data sources as input to the UBEM, as well as to validate results from UBEM. On the other hand, UBEM results also can feed to smart cities projects (e.g., urban energy planning, mitigation of UHI). If UBEM is used in a real-time mode, it can provide timely optimal control and management of building energy demand in response to grid supply.

This paper presents ten questions that highlight some important issues in urban building energy modeling. The proposed answers aim to provide insights into current and future research on urban building energy modeling, and more importantly, to inspire new significant questions from young researchers in the field.

UBEM is entering a new phase of research and application, given more affordable and powerful cloud computing or high-performance computing, and the rapid development of the Internet of Things (IoT), big data, machine learning, and artificial intelligence. We believe, in the near future, UBEM will provide unprecedented value to the design and operation of low-energy buildings and communities in cities. Under this vision, urban buildings will be a key component of digital twins of smart cities, which are virtually designed and tested using urban information modeling, computational simulation, and virtual reality technologies, and will be operated using augmented reality, real-time sensing and metering, and machine learning-driven predictive controls to achieve optimal performance for energy efficiency, sustainability, and resilience.

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