Using Urban Building Energy Modeling to Develop Carbon Reduction Pathways for Cities

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Abstract

Cities have been the nexus of economic activity and growth, but they have an insatiable appetite for energy. In response to the challenges and potential impact of climate change, cities and municipalities around the world are developing climate action plans to reduce carbon emissions and enhance resilience of their built environments. However, policymakers require a data-driven method to identify the most impactful, economical, and feasible strategies – and further translate these to actionable policy levers.
This research serves to democratize and facilitate the wider use of urban building energy models in cities and municipalities.

First, key applications and use cases of urban building energy modeling (UBEM) are identified, and a minimum viable UBEM is introduced for each use case. This framework streamlines computational requirements, data, and calibration needs, promoting more rapid development and utilization of UBEMs. Second, a web-based framework to rapidly generate UBEMs for carbon reduction technology pathways is developed, subsequently piloted in the City of Evanston, and found to significantly reduce time and resources needed for developing and utilizing UBEMs. The approach was further validated in collaboration with policymakers and researchers in eight cities – *viz.* Braga (Portugal), Cairo (Egypt), Dublin (Ireland), Florianopolis (Brazil), Kiel (Germany), Middlebury, VT (USA), Montreal (Canada), and Singapore. Finally, conventional UBEMs typically only incorporate building properties and characteristics. This dissertation also presents an exploratory approach – using supervised and unsupervised data science / machine learning methods – to integrate building properties with socio-economic data from census for better inference and understanding of energy use in cities.

Each approach is documented with the relevant results compared against conventional modelling workflows and / or validated through real-world urban case studies. The major contribution is the development and validation of methods and frameworks that can rapidly and automatically generate UBEMs to help cities and municipalities develop carbon reduction pathways to impact.

Thesis Advisor: Christoph Reinhart
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Chapter 1

Introduction

Urbanization and population growth have proliferated at an unprecedented rate in recent decades, resulting in the densification of urban centers around the world. These urban centers and cities have long been at the nexus of economic growth, innovation, and culture. While these regions collectively occupy less than 10% of the world's landmass, they have an insatiable, disproportionately high appetite for energy. Managing urban building energy use is thus a key strategy to achieving sustainability. In this context, providing a new generation of technological and socio-economic tools and instruments for sustainable and equitable cities is paramount. Accordingly, this dissertation focuses on the development and implementation of tools and frameworks that can support urban scale building energy. A vision for a data-driven urban building energy modeling for sustainable and equitable cities is provided.

1. Introduction

Cities run on energy. Since the industrial revolution, urban environments have been dominating energy consumption patterns in countries around the world. Today – with the dramatic rise in urban population in cities of all sizes (**Figure 1-1**) – over 50% of the world's population lives in urban areas, which collectively generate over 75% of the global gross domestic product (GDP). Attracted by this wealth, the number of urban dwellers is expected to double by 2050. At that point, the urban built-up area is projected to more than triple (United Nations Department of Economic and Social Affairs, 2018), and account for over 75% of global carbon emissions (Intergovernmental Panel on Climate Change, 2014).

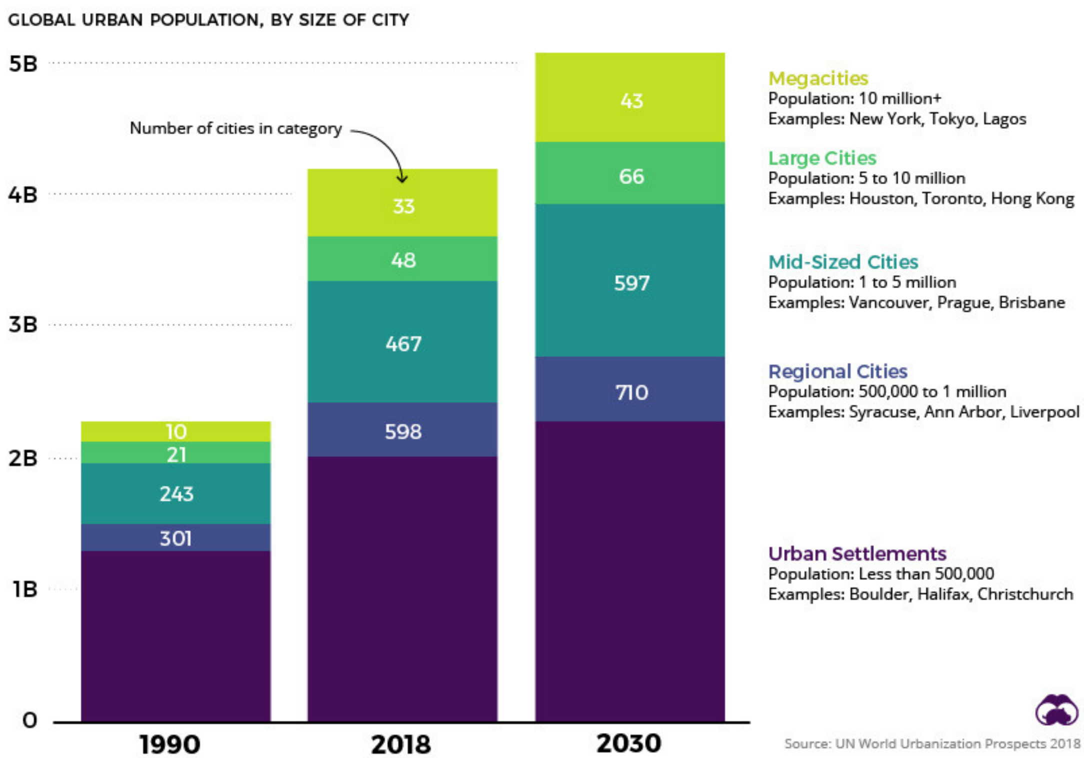


Figure 1-1: Global urban population by size of cities (United Nations, 2018)

Cities are also well positioned to mitigate future emissions, being both "a cause of and solution to" climate change (Milhahn, 2019). More than 100 cities have already committed to net-zero carbon emissions by 2050 (International Institute for Sustainable Development, 2019). Buildings will play a pivotal role in this process with the Intergovernmental Panel on Climate Change (IPCC) estimating that the energy use of existing residential buildings can be reduced by up to 90% in many geographical regions (Intergovernmental Panel on Climate Change, 2014). However, while the stakes are clear, the pathways to achieving carbon reduction targets for buildings are less so. To keep cumulative carbon emissions of the global building stock until 2050 below 300 $GtCO_2$, the annual global renovation rate must increase from the current 1% to 5%, and all new construction must be carbon neutral by 2030 (Weber, Mueller, & Reinhart, 2021). For The United Kingdom, this translates into a retrofit rate of 1.5 homes every minute, from now until 2050 (Timperley, 2018). In the United States, the Biden administration has provided support to upgrade at least four million homes for energy efficiency and weatherize at least two million homes (Urbanek & Shahyd, 2020). To optimize the use of such funds and spur further retrofitting rates to rise to 5%, cities need a decision support framework to decide what type of upgrades to encourage in what buildings. Building new livable urban areas and maintaining existing urban regions can thus be deemed as the defining built environment challenge of the century.

1.2. Urban Building Energy Use

The built environment serves multiple economic and societal needs – we live, work, and play in buildings, and they are pivotal in providing comfortable and productive habitats. Meeting these needs, however, requires significant resources and efforts. The buildings sector accounts for approximately 36% of final energy use and 39% of energy related carbon dioxide emissions (International Energy Agency, 2019). Both percentages are currently rising. Naturally, electricity for space conditioning, lighting, appliances, and equipment is the fastest growing energy source in residential and commercial buildings. Additionally, current living habits and lifestyles of urbanites are largely unsustainable, and demand for natural resources are at an all-time high – and continuing to grow. The finite nature of energy-related and other associated resources means that cities must effectively manage resource consumption. In this context, urban built environments are a prime target for emissions mitigation.

For the built environment, this means that we must better grasp how much energy each building in a geographical area or jurisdiction uses, and what the required costs and upgrades would be to reduce its energy use. We also need to convince policy makers, administrators, and building owners to promote the most impactful and cost-efficient measures by devising policy levers and programs that trigger these measures into action. Finally, future building stock models need to be integrated with the existing energy supply, distribution, and transmission infrastructure to ensure long-term stability and sustainability. In short, we need a new, effective decision support framework for buildings, especially at the urban scale.

Urban building energy modelling (UBEM) is a bottom up, physics-based approach to simulate the thermal performance of multiple buildings that has been developed to serve as the analytical backbone for the decision processes laid out above. The field has flourished in recent years, leading to increasingly robust urban data streams that start from geographic information systems (GIS), light detection and ranging (LiDAR) and tax assessor databases and end in synthetic hourly building energy demand profiles for current and potential future conditions. Depending on the availability of historic building energy use data, a variety of modeling, simulation, and calibration approaches have been developed. At the same time, different UBEM use cases have been put forward both in academia and practice.

1.3. Research Problem

While UBEM provides a myriad of opportunities and has immense potential to be an integral toolbox for cities to achieve sustainability or carbon reduction goals, there exist several problems impeding its adoption and implementation. First, there are different UBEM use cases put forward both in academia and practice especially in recent years. The result is a somewhat confusing plethora of UBEM modelling methods for researchers, urban planning teams, energy policy makers, utilities, and building owners to choose from (or rather, get lost in). Additionally, UBEMs typically require an elevated level of technical know-how and significant amounts of effort and time to develop, rendering them out of reach for typical policymakers and city planners – especially those from mid-size to smaller cities and municipalities – who possess neither the resources nor the technical expertise or time.

Furthermore, data required to develop these UBEMS becomes significantly tedious to obtain at the urban scale. In the United States, counties and cities / towns mostly manage their built environment datasets independently using their own open data platforms. Coupled with the many file formats for storing and transmitting data, this becomes a significant impediment for policymakers, researchers, and practitioners looking to develop robust UBEMs to support policymaking. Finally, typical UBEMs incorporate only technical characteristics pertinent to building science and its associated construction properties / assemblies without considering socio-economic parameters critical to successful policy application and adoption. Incorporation of these considerations could result in more robust, representative UBEMs with simulation results reflecting the energy use profiles aligned with the demographics in the region.

1.4. Research Hypothesis

The hypotheses underlying this thesis are that the streamlining of UBEM use cases, development of automated UBEM generation and visualization tools, and incorporation of socio-economic information into UBEMs are feasible. These can be integrated into the policy design and development process for cities and municipalities around the world, at a justifiable effort level, while providing relevant results for policymaking towards sustainable and equitable cities and society.

Feasibility

- UBEM is an effective tool to help policymakers make data-driven, informed policy decisions. Streamlining UBEM workflows and enhancing accessibility to UBEMs will empower policymakers to use them as part of their policy development process, especially to identify potential technology pathways towards energy efficiency and carbon emissions reduction.
- Conventional UBEMs typically only incorporate properties and characteristics of buildings, but socio-economic factors have an impact in energy use patterns (especially in residential units). It is feasible to integrate this information in UBEMs for better inference and understanding of the building stock.

Justifiable effort

- If UBEM use cases are properly defined and automated, and user-friendly tools are available, the additional effort that is required for each city / municipality to generate UBEMs and use them to make data-driven decisions are marginal. The benefits reaped by cities from utilizing these UBEMs will henceforth be justifiable.

Relevance

- UBEM analysis are relevant to the policymaking processes.
- Conventional UBEMs typically assign archetypes by program and age, with a general occupancy profile assumed for all residential buildings – and do not consider demographics. However socio-economic factors are relevant factors that will affect household level energy / electricity use, and should be incorporated and considered in UBEM analysis.

1.5. Dissertation Outline

This dissertation presents and validates use cases of UBEM and a framework to rapidly generate UBEMs for policy design, and explores how socio-economic parameters / variables can be incorporated in conventional UBEMs. The framework was validated and utilized by policymakers in eight cities around the world with varying climates and policy objectives.

Chapter 1 provides an introduction and a brief overview of the scope of the dissertation and its motivation, focusing on utilizing UBEMs for policymaking towards sustainable and equitable cities.

Chapter 2 describes the current process for developing UBEMs in the context of existing techniques, as well as data requirements and data sources. This chapter also introduces the concept of a minimum viable UBEM, adapted from and conceptualized in the spirit of modern technology start-ups.

Chapter 3 consolidates UBEM applications and proposed four key use cases for UBEMs, each with different requirements, data fidelity, targeting different user groups. A minimum viable UBEM is described for each use case.

Chapter 4 introduces UBEM.io, a web-based framework to rapidly generate UBEMs for carbon emissions reduction pathways. The technical implementation of UBEM.io – including the frontend, backend, and APIs – is described. The framework was pilot tested in an area in the city of Evanston, and significant efficiency gains were achieved over conventional UBEM construction and development methods.

Chapter 5 describes a collaboration with policymakers from eight cities around the world, using UBEM.io to develop seed UBEMs. These seed UBEMs supported the cities in identifying and assessing carbon reduction technology pathways for building energy use. The building technologies and associated pathways selected by policymakers in each city are examined, together with the implications in terms of energy usage intensity and carbon emissions reduction.

Chapter 6 proposes a novel methodology to integrate conventional building physics-based UBEMs with socio-economic variables from census data, using supervised and unsupervised machine learning. Data from smart meters are first clustered to provide residential load profiles, following by the development of a tree-based classification model to better understand variable / feature importance.

Finally, the hypotheses are revisited in *Chapter 7*, followed an outlook of future next steps.

Chapter 2

State of the Art

The following chapter describes the state of the art in the context of the UBEM process, the various geometric and non-geometric data required, as well as the stages involved in an UBEM development pipeline. The chapter also introduces the concept of a minimum viable UBEM.

Elements of this chapter have been published in the *Applied Energy* journal:

Yu Qian Ang, Zachary Michael Berzolla, Christoph F. Reinhart (2020). From concept to application: a review of use cases in urban building energy modeling. Applied Energy 279.

2. State of the Art

2.1. Urban Building Energy Modeling

The basic concept of an UBEM is to apply physics-based, individual building energy models (BEM) to hundreds or even tens of thousands of buildings. BEMs are coupled heat transfer and mass-flow calculations whose core simulation engines trace back to the 1970s (Mills, 2004). BEMs have become increasingly cost-efficient and are now routinely used during the planning and design of high-performance buildings. While the underlying physics are identical for BEM and UBEM, the latter requires significant automation procedures and computational prowess during data input, model generation, simulation, and execution. BEMs is now being used widely around the world, in industry, research, even policymaking, but UBEMs are primarily restricted to research and academia. Modern, automated UBEM calibrated against measured data (if available) can reduce laborious manual work across various stages, and boost computational efficiency. **Figure 2-1** illustrates the steps, data sources, and data formats that are typically involved in an UBEM workflow.

During the *Planning* step, overall project objectives and end uses should be clearly defined, with the required data sets and simulation steps identified for the project at hand. This step thus determines the project's application type. The four application types are introduced below, and further explained in subsequent sections of this chapter.

As the name suggest, *Data Pre-processing* involves locating and securing various urban and built environment data sets necessary to build the eventual UBEM. Common geometric formats such as LiDAR point clouds or GIS shapefiles define spatial and geometrical properties of a neighbourhood or city of interest. Alternatively, urban building geometries can also be derived from point coordinates, geographical or vector features in file formats such as CityGML (OGC, 2020) or GeoJSON (IETF, 2020). CityGML is an open data model and XML-based format for storage and exchange of digital 3D models of cities, while GeoJSON is an open standard format that encodes geographical data structures using the JavaScript object notation. Other geometric parameters such as window-to-wall ratio (WWR) for different façade orientation are generally unavailable at the urban scale, and somewhat tedious to collect manually. However, they can potentially be estimated from street-view or satellite images (Cao, et al., 2017) or inferred based on building age and type. For new neighbourhood designs, building massing models are provided by the urban design team.

In addition to building geometry, so-called non-geometric properties of buildings in an area of interest are required as well. These properties range from construction assemblies to equipment descriptions and usage schedules. They can often be assembled from various sources, such as property tax assessment data in the U.S. or the TABULA database (Tabula, 2020) in Europe. In many cases, rather than making explicit assumptions for each building, the existing building stock is segmented into archetypes or categories based on program type, building age, and / or characteristics. Archetypes are composite representations of buildings in an area, with relatively similar parameters and attributes. Archetypal segmentation makes the process of modeling hundreds to thousands of buildings more manageable.

A representative building parameter template then needs to be developed for and applied to each archetype. As described under the *Calibration* step, depending on the application type, templates and the generated energy demand profiles may later undergo additional calibration procedures. Template information is often defined somewhat anecdotally by simulation experts with intimate knowledge of current and past local construction practices. Since data for stock-wide, building-by-building performance properties and construction assemblies are rare to non-existent and extremely laborious to collect, information from other data sources such as property tax assessment data or building audits may be used to fill knowledge gaps and generate complete building parameter templates. For example, blower door tests in selected buildings may connect infiltration rates with the date of last renovation or owner-occupied versus rented status. Hourly weather data, another important input component for UBEM, may either be used in the form of a typical meteorological year (TMY) collected at a nearby weather station or synthetically generated / transformed (Bueno, Norford, Hidalgo, & Pigeon, 2013) to include urban heat island effects, local wind patterns, and/or future climate change predictions (Jentsch, James, Bourikas, & Bahaj, 2013).

In general, *Data Pre-processing* entails sourcing data, cleaning and addressing gaps which are common in datasets sourced from public open platforms. Subsequently, datasets from various sources need to be synchronized or combined into a “simulation ready” state. For example, in the case of two-dimensional (2D) shapefiles with building footprints, additional information such as property tax assessment data with building floor area, number of bedrooms, number of levels, and/or floor-to-floor heights can be used to infer / estimate overall building heights and extrude the building footprints to construct 2.5D or 3D urban models. Building heights, zoning type, and other information can be embedded as attributes for the building footprint polygons through methods such as spatial join in GIS software, or as accompanying files in formats such as comma separate values (CSV). Alternatively, building heights can also be obtained from LiDAR point cloud or digital surface model (DSM) files. Interoperability between software environments is important now since the datasets likely come in various formats from dissimilar sources.

Model Generation usually involves BEM creation for all archetypes and building profiles once the data is in a "simulation ready" state, with the output being the main urban building geometry file and accompanying non-geometric properties. Nowadays, this process tends to be highly automated.

During *Simulation,* hourly (or higher time-step resolution) profiles of conditioning and equipment loads as well as indoor temperature are generated and may be further converted into energy use and associated carbon emissions. The conversion from thermal loads to fuel to carbon emissions can happen in a variety of ways from using static coefficients of performance of all HVAC equipment to more detailed system models (Cho, Mago, Luck, & Chamra, 2009) (US EPA, 2020). As with *Model Generation*, *Simulation* is nowadays usually largely automated through software programs or scripting.

Depending on the application type, model *calibration* may be necessary. Calibration is the process of harmonizing simulation outputs with any measured energy data. The process necessarily applies to existing buildings that may undergo future retrofits, and is usually iterative, aimed at reducing uncertainty until the discrepancy range falls within prescribed acceptable tolerances. Common measurement metrics to determine the degree of confidence in individual building energy models include normalized mean bias error[1] (NMBE) and the coefficient of variation of the root mean square error CV (RMSE), which measures the variability of errors between simulated and measured values. Target levels for NMBE and RMSE at the individual building level are provided by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Guideline 14 (ASHRAE, 2014), the Federal Energy Management Program (FEMP) Measurements and Verification (M&V) Guidelines (Coakley, Raftery, & Keane, 2014), and the International Performance Measurement and Verification Protocol (IPMVP) (EVO, 2016). Most academic and research works adapt BEM-level metrics as above for UBEM-level calibrations, and there is no universally adopted benchmark or measurement metric system for UBEM. Due to the considerable number of parameters involved in model calibration, the process has historically been both time-intensive and somewhat inconclusive, since multiple input parameter combinations can often yield results close to the measured energy use (over-parameterization). Models that are overly complex may also be prone to overfitting, with the resultant UBEM not generalizable to other areas. While the degree of UBEM calibration *possible* depends on the availability of energy data, the calibration level *justifiable* and *required* depend on the

[1] The normalized version of the mean bias error which aggregates errors of a sample space

UBEM application type, as over-specification or over-fitting can lead to diminishing benefits or no benefits at all. As it stands today, with UBEMs still an emerging research field, the calibration method selected tends to be largely driven by data availability and judgement of the researcher / practitioner.

A calibration approach that is commensurate with the target UBEM application type is necessary. For example, un-calibrated UBEMs or UBEMs calibrated based on only a subset of buildings for which energy data is available are usually fully capable of predicting neighborhood-wide energy use or energy use intensity distributions, respectively. While such models may exhibit simulation errors as high as ±90% at the individual building level (Ahmad & Culp, 2006) (Li, Yang, Becerik-Gerber, Tang, & Chen, 159), their accuracy is perfectly adequate for urban planning or stock-level carbon reduction strategies, rendering higher effort calibrations at the individual building level unjustified.

2.2. Research Gap

Several studies (Abbasabadi & Ashayeri, 2019) (Johari, et al., 2020) (Sola, et al., 2020) have reviewed UBEM literature and tools. Most, however, adopts a top-down (statistical) and bottom-up (physics-based) lens, with actual applications unclear. Cities and their associated built environments come in different shapes and sizes, and projects range from conceptual studies with parametrically changing building massing to detailed analyses of stock models – each having different data fidelity requirements. The current top-down / bottom-up lens is thus unable to depict various use cases and applications.

The process laid out in this section – as with **Figure 2-1** – is an "all-out", complete process targeted at developing a detailed UBEM will full parameter sets. This paradigm seemingly resulted in researchers rushing to developed UBEMs as detailed as possible, using the most modern, sophisticated techniques. This may often be unnecessary especially for simpler use cases and / or city and municipalities without technical expertise or resources. The process is also devoid of any considerations for social-economic parameters, primarily incorporating data pertaining to building characteristics.

The factor above highlights the gaps in existing research – while computational tools for UBEMs may be advancing, use cases (and their end-users) are unclear, impeding actual applications. This is further exacerbated by a lack of understanding and integration between the technological and socio-economic aspects. The next chapter categorizes key UBEM use cases into four main applications, and introduces the concept of the minimum viable UBEM developed as part of the research in this thesis.

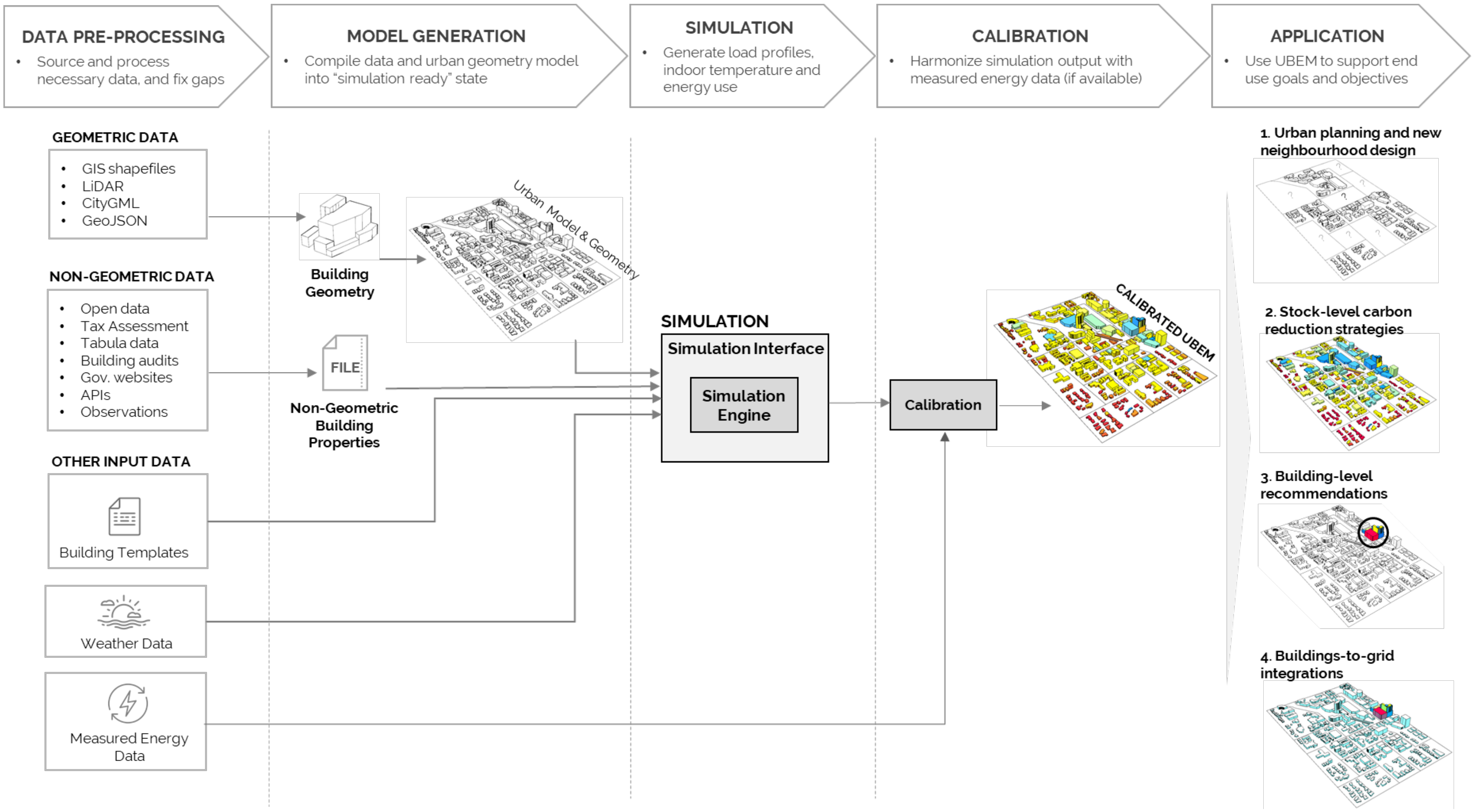


Figure 2-1: UBEM workflow, processes, and data streams.

Chapter 3

Use Cases of Urban Building Energy Modeling and The Minimal Viable UBEM

This chapter organizes UBEM use cases in industry, policy, research, and academia into four main application categories – i.e., urban planning and new neighbourhood design, stock-level carbon reduction strategies, individual building-level recommendations, and buildings-to-grid (B2G) integration. For each application, the chapter further introduces a minimum viable UBEM (MVU), a novel concept for UBEMs conceptualized in the spirit of a minimum viable product (MVP) in modern technology start-ups. Specific case studies and / or examples are listed for each application area where available.

Elements of this chapter have been published in the *Applied Energy* journal:

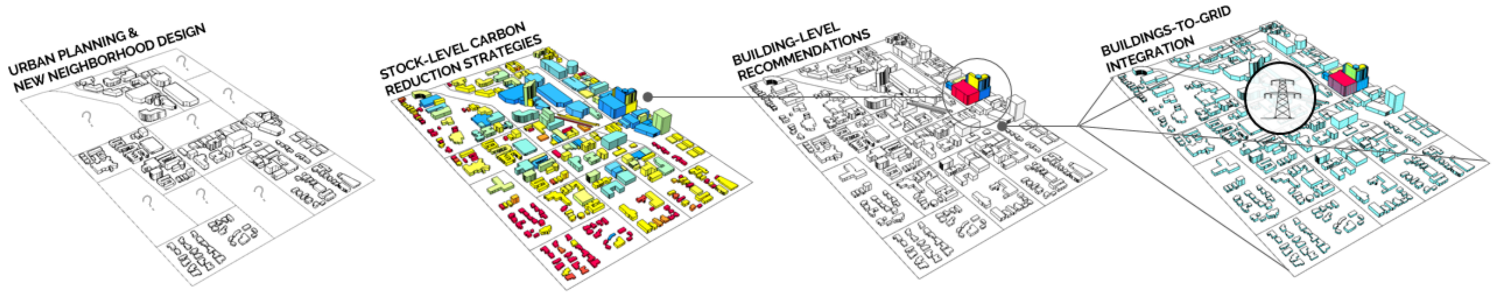
Yu Qian Ang, Zachary Michael Berzolla, Christoph F. Reinhart (2020). From concept to application: a review of use cases in urban building energy modeling. Applied Energy 279. https://doi.org/10.1016/j.apenergy.2020.115738

3. UBEM Application and Use Cases

The goal of this chapter is to organize UBEM use cases into four main application types, namely urban planning and new neighbourhood design, stock-level carbon reduction strategies, individual building-level recommendations, and buildings-to-grid (B2G) integration. For each application scenario a so-called *minimum viable UBEM* (MVU) is introduced, that can reliably answer the question at hand. As the name suggests, such a model provides an appropriate level of data input, as well as simulation and calibration effort based on the application at hand, while avoiding unnecessary over-specification of parameters. Requirements for each application, as well as the minimum viable UBEMs, are summarized in **Figure 3-1**, and further discussed.

3.1. The Minimum Viable UBEM

The minimum viable UBEM (MVU) concept follows the logic of a minimum viable product (MVP) (Ries, 2011) popularized by the rise of modern-day lean technology start-ups and rapid prototyping methodologies. The main intent is to use just enough detail to develop a working model that provides immediate value and allows for rapid early utilization, while minimizing effort and cost. The MVU sets the baseline for further development, allowing users to test assumptions and clarify required complexity in subsequently stages. In some cases, the MVU can also be used to showcase future potential and gain buy-in so that important stakeholders, such as policy makers or building owners, can see the promise or vision of the final model and thus provide support or resources for its realization. For example, once a municipality develops a high-level carbon reduction strategy for its constituents and builds political consensus that building retrofitting is a worthwhile cause, a more costly building-level recommendation model may become an option. Similarly, a new neighbourhood model based on generic building parameter templates may initially be used to develop a vision of how buildings and their associated energy supply may work together. Such generic templates may subsequently evolve into more customized BEMs as different architecture teams start working on individual buildings within a larger master plan.



	1. Urban planning & new neighbourhood design	2. Stock-level carbon reduction strategies	3. Building-level recommendations	4. Buildings-to-grid integration
PLANNING				
Main Users	Urban planners, architects, policy makers, planning consultancies, etc.	Municipalities and agencies, city planners, policy makers, planning consultancies, etc	Building portfolio owners, individual building owners, facility managers, energy consultancies	Utilities, grid regulators, distribution and transmission system operators
Use cases / Objectives	- Massing studies - Analysis of system designs & options - Window-to-wall ratio or glazing studies - Value engineering for new construction - Others	- Energy policy interventions - Carbon reduction strategies - Building stock retrofit studies - Incentive programs analysis - Others	- Building-level retrofit studies - Analysis of energy savings potential - Specific building-level upgrades - Benchmarking studies - Others	- Grid stability studies - Demand response analysis - Load modifying interventions - Transmission/distribution system analysis - Others
DATA AND MODEL				
Geometry	Simple massing (unless otherwise needed)	Representative geometry (e.g. GIS, CityGML)	Representative geometry (e.g. GIS, CityGML)	Representative geometry (e.g. GIS, CityGML)
Building Templates	Generic	Generic or Archetype level with customizations	Archetype or Building level with customizations	Archetype or Building level with customizations
Weather Data	✓	✓	✓	✓
Measured Energy Data	x	Data from some buildings (annual, monthly, daily)	Building level (monthly, daily, hourly, sub-hourly)	Building level (daily, hourly, sub-hourly)
SIMULATION				
Reliable Outputs	Neighbourhood/Precinct EUI	Annual EUI distribution (medium fidelity, time-step, and uncertainty)	Building level (high fidelity, small time-step and less uncertainty)	Building level (highest fidelity, small time-step, less uncertainty)
CALIBRATION				
Calibrated model	x	A. No calibration B. Archetype level calibration	A. Archetype level calibration B. Building level calibration	A. Archetype level calibration B. Building level calibration
Calibration methods	x	Statistical tools, Bayesian/semi-Bayesian, machine learning, etc.	Surrogate/auto-calibration, statistical tools, Bayesian/semi-Bayesian, machine learning, etc.	Potential new genre of calibrations

Figure 3-1: Four main UBEM applications and their respective process and data requirements

3.2. UBEM for Urban Planning and New Neighbourhood Design

Urban typology has a significant influence on building energy use through numerous factors such as geometry, typology and form (Pisello, Taylor, Xu, & Cotana, 2012), as well as shading, daylighting and the urban heat island effect (Giridharan, Lau, Ganesan, & Givoni, 2007). The process of shaping and giving spatial relationships or features to cities, townships, and neighbourhoods is often iterative and multi-disciplinary, integrating disciplines such as design, engineering, economics, and politics. In this context, urban planners and policy makers can leverage UBEMs to gain a quick understanding of the energy and carbon trade-offs between different urban forms and their associated attributes. This can be studied in conjunction with a full range of urban planning considerations and technical design aspects, such as land use, zoning, urban economics, transportation, standards, codes, and safety and security.

For new neighborhood design, urban planning teams typically start with a terrain model of the site as well as massing models from nearby buildings. The massing models of new, proposed buildings are then generated from scratch and archetype templates are assigned through high-level rules such as retail at the bottom (podium block) and multi-unit residential above (tower block). Given that the modeled buildings do not actually exist, a new neighborhood UBEM is mainly used to iterate through a variety of building massing layouts, WWR constellations, and program mixes. Figure 3-2 illustrates an example of using UBEMs to rapidly prototype assorted options for new neighborhood design and planning. The purpose of such a comparative analysis is to understand relative performance of various planning permutations, not to predict actual future energy use. The underlying archetype templates should therefore be realistic, and yield results comparable to similar neighborhoods, but no explicit calibration is required or even possible.

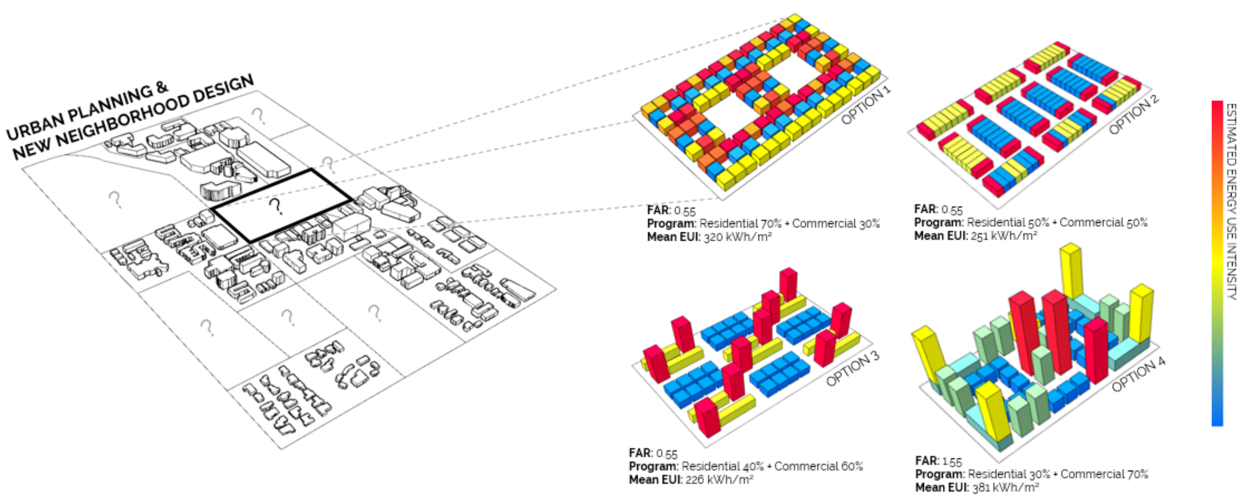


Figure 3-2. Example of how UBEMs can be used to rapidly prototype options for new neighbourhood planning, with parameters modelled for an area in Cook County, Illinois.

Specific use cases on utilizing UBEMs for urban planning and new neighbourhood design are shown in **Table 3-1**. Kohn Pedersen Fox, an architecture and urban planning practice, incorporated energy parameters as a performance metric in a generative urban design workflow and applied the methodology to three areas in China and Canada (Wilson, Danforth, Cerezo Davila, & Harvey, 2019). Another study outlined a process for categorizing an urban area into 50 to 100 generalized models, as part of an urban masterplan for energy reduction over a 30- to 40-years trajectory (Marston, Garforth, Fleichammer, & Baumann, 2014). Sehrawat & Kensek (2014) devised a workflow to treat GIS data as multiple building information models (BIM), and used simplified massing, scripting, and customized templates for neighbourhood level energy simulations. Heiple & Sailor (2008) combined bottom-up simulations for prototypical buildings with geospatial GIS data to estimate energy consumption profiles for buildings in Houston, and proposed for the model to be applied to urban scale atmospheric modelling purposes to better understand effects on urban heat island and air quality. Fonseca and Schlueter (2015) introduced a model to characterize spatiotemporal building energy consumption in neighbourhood and city districts. This model identifies present and potential states of building energy consumption due to urban transformation, and the authors further proposed for urban planners to utilize the model to study impacts of urban forms.

An UBEM developed for urban planning and new neighbourhood design can be an important part of the overall cost-benefit and impact analysis toolkit for urban planners and city policy makers. It possesses multiple functionalities to address important urban design, planning, policy, and economic considerations. For example, urban planners can rapidly analyse design options in a parametric or generative manner, study impact of various design and planning options on potential energy use, and benchmark energy performance of the proposed built-up area in relation to existing planning policies or standards. By utilizing UBEMs, planners and policy makers can quickly understand how potential energy demand can be balanced with other key factors – such as mobility, economics, resilience, and housing needs – and identify potentially problematic areas or segments where high value capture can occur with relatively low cost and / or effort. Lastly, these UBEMs can also help predict potential carbon emissions of new neighbourhoods through relatively simple calculations, or to investigate potential value of technology deployment such as solar photovoltaics (Zhai, Larsen, Millstein, & Masanet, 2012).

3.2.1. The Minimum Viable UBEM for Urban Planning and New Neighbourhood Design

Due to the iterative (and often early-stage, conceptual) nature of the process, an ideal minimum viable UBEM for urban planning and new neighbourhood design should utilize relevant standard and/or customized building parameter templates for new construction, as well as weather files appropriate for the climate, geography, building typology, and design parameters. The UBEM should not be overly complicated and detailed, since adding unnecessary complexity for a broad and iterative task impedes the realization of simple solutions and analyses.

The minimum viable UBEM at this stage can therefore be as simple as using publicly available spatial datasets to construct the existing urban building geometry for context and urban microclimate studies, apply standard weather files, and subsequently select, customize, and assign appropriate building parameter templates for simulation. In the United States, a good starting point for such investigations are the US Department of Energy (DOE) Commercial Reference Buildings for New Construction (US Department of Energy, 2020), which provides reference building parameter templates by building type and climate zone / representative city. Many planning authorities or GIS departments at state, county, or city level also provide open data in the form of GIS shapefiles. These shapefiles include building footprints, jurisdiction or municipality boundaries and districts, street centrelines/midlines, and others, which, together with information on building heights or number of levels, are sufficient to construct an urban context geometry model.

Table 3-1: Examples for urban planning and new neighbourhood design

City/Region	Input Data Type or Source	Target Use / Application	Target Users	Modeling / Simulation Tool(s)	Calibration Level	Accuracy or Uncertainty	Source / Reference
Hangzhou (China) Toronto (Canada) Southern China	Pixel maps, street networks, block polygons	Master-planning urban design and planning	Urban planners, architects	Rhinoceros3D, Grasshopper, custom scripts, and interfaces	None / Not found	None / Not found	(Wilson, Danforth, Cerezo Davila, & Harvey, 2019)
A Naval Shipyard (USA)	Walkthrough of the site, and interviews with facility managers	Current and future energy use of the community	Municipalities, community policy makers	Generalized energy models	None / Not found	Model not designed to match	(Marston, Garforth, Fleichammer, & Baumann, 2014)
Los Angeles (USA)	GIS database, gbXML templates, Revit and eQuest models, reported data	Evaluate building energy characteristics for urban areas	District or municipal organizers and policy makers	GIS environment, eQuest, Revit and Green Building Studio	None / Not found	Percent difference from various models ranges from 4% to 35%	(Sehrawat & Kensek, 2014)
Switzerland	Urban GIS, archetype and distributional data from official databases, open street maps, local building standards and other studies	Urban and energy planning, assessment of potential energy efficiency measures	City and urban planners, policy makers	Custom framework built on top of ArcGIS	None / Not found	4% to 66% error for energy services, validated against measured data	(Fonseca & Schlueter, 2015)
Turin & Stockholm (Italy & Sweden)	GIS tools, census data, statistical data, load curves from existing networks	Urban space heating demands and efficiency measures for scenarios up to 2050, energy policies	District / city planners, policy makers	GIS tools with census data, statistical instruments, and building audits	None / Not found	None / Not found	(Delmastro, Martinsson, Mutani, & Corgnati, 2017)
Houston (USA)	GIS and tax lot data, and existing building information from RECS and CBECS.	Urban scale atmospheric modeling for urban heat island and air quality studies	City planners, municipalities	eQUEST with DOE-2 engine	None / Not found	Simulated EUIs within 10% of existing building types	(Heiple & Sailor, 2008)

3.3. UBEM for Stock-Level Carbon Reduction Strategies

As mentioned in the introduction, many cities world-wide have adopted ambitious carbon reduction goals, with many reaching all the way to carbon neutrality in the coming decades (McKinley & Plumer, 2019). To implement these aspirational goals for their building portfolio at urban scales, cities should at a minimum understand what energy savings certain building upgrades would yield if applied to all buildings of similar program type, age, category, or archetype (for example, single-family homes built before 1980). This information can be extracted from the same uncalibrated templates that were discussed for the urban planning application, with the difference being that these templates are assigned to existing buildings as well as potential infills. Energy savings from various upgrades can then be estimated by replacing "as is" templates with new templates that reflect these upgrades. The model and simulation results will then show the total carbon reduction potential for various retrofit scenarios, including which building type(s) contribute most significantly to these savings (**Figure 3-3**). One of the first city-wide UBEM for a major city that was built in this manner was for the City of Boston using publicly available GIS datasets (Cerezo Davila, Reinhart, & Bemis, 2016).

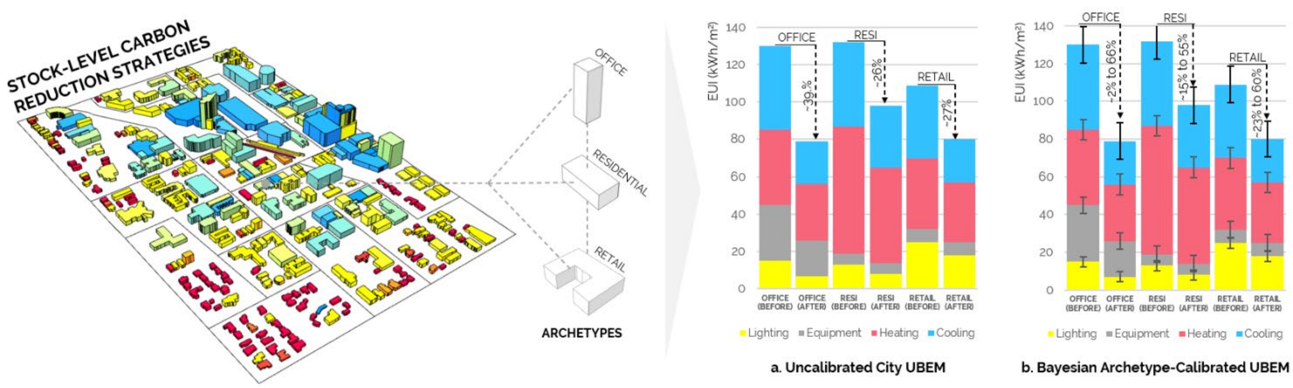


Figure 3-3. Example of using uncalibrated and Bayesian calibrated UBEMs to study energy savings potential for various archetypes in a simulated area in Cook County, Illinois.

A limitation of the abovementioned uncalibrated UBEM of an existing city is that it remains unclear what the range of savings for different buildings within a category, program type, or archetype would be. The deterministic, fixed values for simulated energy use and potential savings may also experience significant inaccuracies as explained in section 2. For example, it is widely accepted that occupant behavior – such as intensity of use and thermostat settings for HVAC systems – have a critical impact on energy use and potential savings. This behavior varies significantly for different buildings even within the same archetype. For example, a study using sensitivity analysis with UBEMs in an area comprising 284 buildings in Switzerland found that cooling demand is most strongly influenced by setpoint temperature (Mosteiro-Romero, Fonseca, & Schlueter, 2017). Another study found that models considering stochastic – rather than deterministic – occupant behavior can better capture realistic spatiotemporal energy demand patterns at district levels (Happle, Fonseca, & Schlueter, 2018). In this vein, ASHRAE created a working multidisciplinary task group on occupant behavior in buildings (MTG.OBB). MTG.OBB is tasked with coordinating technical activities and facilitating development of research, tools, data guidelines, and technologies to better integrate information pertaining to occupant behavior in the design, operation and retrofit of new and existing buildings. Examples of completed and ongoing projects undertaken by the task group include seminars, development of position papers, and handbook chapters on occupant-centered HVAC design and data collection (ASHRAE, 2017).

Although different behaviors in even the same building type / archetype tend to average out if all buildings are evaluated concurrently, not all buildings will be upgraded at once in reality. To identify a reliable set of energy saving measures and to formulate effective retrofit incentive programs, policymakers will benefit from an uncertainty analysis along with the associated energy saving predictions – where energy savings potentials are presented across a plausible savings range or confidence interval, rather than fixed values that may not be accurate. To this end, measured energy data for a representative subset of buildings in an UBEM is required. Using Bayesian / semi-Bayesian archetypal calibration techniques (Sokol, Cerezo Davila, & Reinhart, 2017), a modeler can single out key simulation parameters from a building parameter template that are difficult to predict. From there, the modeler can create likelihood distributions for these parameters based on buildings with measured energy data. Once these parameter distributions have been established, energy savings for any other buildings belonging to the same archetype can be calculated by conducting multiple simulations of each building for different parameter realizations with and without energy upgrades. This in turn leads to a distribution of savings for each building. Combining these building-level predictions into ensemble models for different archetypes has led to reliable energy use intensity and savings distributions and estimates, which can be presented as a range of possible savings for a whole neighborhood (**Figure 3-3b**) or shown for each building individually. **Figure 3-4** illustrates potential savings for envelope and envelope + lighting upgrades for a sample of 100 buildings with vintages – pre- and post-2000 – in Cook County, Illinois. Typical energy conservation measures (ECM) for envelope include weatherization and glazing, façade, and/or insulation upgrades, and common lighting ECMs include energy saving light emitting diode (LED) or eco lighting fixtures together with occupancy sensors. Such a method for UBEM modeling, calibration and analysis is detailed in a study done by Cerezo Davila, Jones, Al-Mumin, Hajiah, & Reinhart (2017), and further elaborated in Reinhart & Cerezo Davila (2019).

This information is highly actionable, since it helps municipalities decide which policy lever or incentive program should be prioritized for greater impact. For example, envelope upgrades in post-2000 buildings in **Figure 3-4** would yield approximately ~5% savings on average, and may risk obtaining little to no savings with significant cost implications. In contrast, upgrades to lighting may result in a better return on investment. By examining the profile of buildings in the study area and carrying out such studies, planners and policymakers can conduct cost-benefit analyses to yield the highest certainty of energy or cost savings.

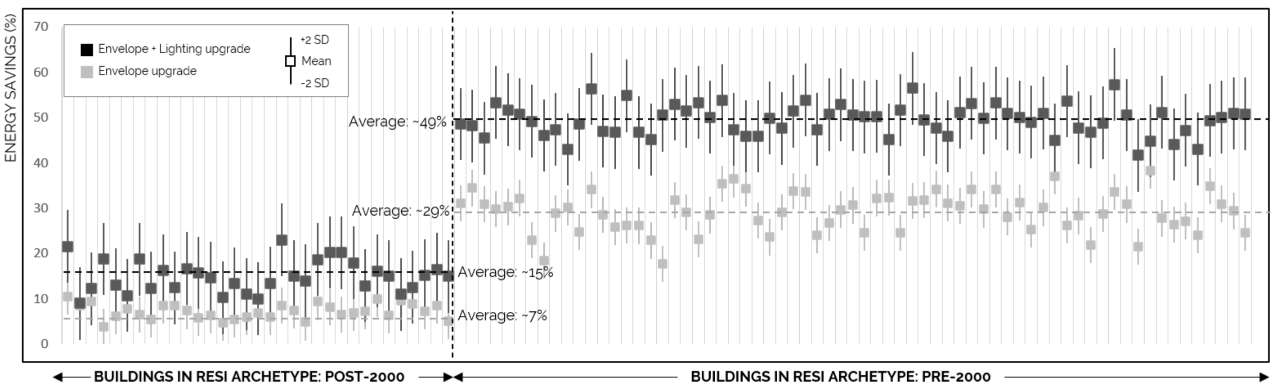


Figure 3-4. Energy savings potential of a sample of 100 buildings in Cook County, Illinois, as in Figure 3-4, for envelope and envelope + lighting upgrades

Table 3-2 lists comparable studies on stock-level energy management and carbon reduction strategies. Nouvel et al. (2015) used a combination of statistical and engineering-based methods for approximately 1,000 buildings in Rotterdam and found that the prediction displayed good agreement with measured data at neighbourhood level, but errors became higher at disaggregated levels. Pasichnyi, Wallin, & Kordas (2019) devised a methodology for characterizing archetypes for 5,532 buildings and applied it for two main use cases in Stockholm to identify potential energy savings via retrofitting and explored the potential for reducing electric heating power demand.

A calibrated UBEM developed for stock-level carbon reduction strategies and energy management will require considerably more effort, but can help policy makers, practitioners, and researchers better understand energy use across different building types. These results can be compared against benchmarks, and the potential of energy policy levers, such as incentive or retrofit programs, can be analyzed in greater detail. These UBEMs can also support relevant studies, including but not limited to the impact of urban heat island effect or the installation of renewables such as photovoltaics.

3.3.1. The Minimum Viable UBEM for Stock-Level Carbon Reduction Strategies

The creation of an uncalibrated stock-level UBEM is relatively straightforward and can offer valuable initial insight into how much carbon emissions a municipality can expect from different upgrades in total. Required geometric datasets are typically available so most of the work for the modeling team is to come up with meaningful building stock templates and upgrade scenarios, as well as to link geometry data with zoning, tax assessor, and / or other datasets that facilitate assigning appropriate archetypes to each building in the UBEM.

The data sources and workflow to develop an urban building geometric model can follow the process outlined in the previous section, where building footprint shapefiles or CityGML data can be obtained from open data platforms. In this context, it will be wise to ensure that the relationships between points, lines, and polygons are coherent and accurate for the original geometric files and resultant urban geometry. This will ensure that thermal zones for simulations can be properly generated from the geometries.

Archetypal calibration based on statistical / Bayesian methods using a subset of metered energy data offers better risk analysis but requires significantly more effort and expert-level knowledge. Based on the time resolution and fidelity of metered data, calibration can be conducted annually or monthly. Being able to predict seasonal savings may be particularly interesting for the residential buildings which tends to have the larger variations in summer and winter peak loads than commercial or industrial buildings. In the US, seasonal peak loads for all residential buildings combined can range – between the lowest and highest recorded – by as much as 67 billion kW (US EIA, 2020).

Table 3-2: Examples for stock-level carbon reduction strategies and energy policies

City/Region	Number of buildings	Input Data and/or Source	Target Use / Application	Target Users	Modeling / Simulation Tool(s)	Calibration Level	Accuracy or Uncertainty	Source / Reference
Boston (USA)	83,541	GIS files, tax assessment records	Energy policy, district level interventions, demand management	Municipality, development authority, policy makers	Rhinoceros3D + custom grasshopper components to access EnergyPlus	None / Not found	Error of averaged modeled EUI ranged between 5% to 20% compared with CBECS	(Cerezo Davila, Reinhart, & Bemis, 2016)
Stockholm	5,532	Energy performance certificates and measured factual data	Identify potential for reducing heat energy demand through retrofitting, explore electric heating and potential to increase local grid capacity	Utilities, city planners, policy makers	Statistical and physics-based modeling using R and DesignBuilder	Archetype	Most results within ASHRAE Guideline 14 for MASE, NRMSE and R^2	(Pasichnyi, Wallin, & Kordas, 2019)
Kuwait	336	GIS files from city, building documents, metered energy demands	Support urban energy efficiency strategies	Utilities, policy makers	R, Rhinoceros3D + custom grasshopper components to access EnergyPlus	Archetype	Maximum error of 15% in 10^{th} and 90^{th} percentile for best performing model (Bayesian calibrated)	(Cerezo Davila, Jones, Al-Mumin, Hajiah, & Reinhart, 2017)
Cambridge (USA)	2,662	GIS files, tax assessment records, measured energy consumption	Assess retrofit strategies and energy supply options	City planners, utilities	R, Rhinoceros3D + custom grasshopper components to access EnergyPlus	Archetype	16.5% of buildings unexplained when calibrating to monthly data vs <1% when using annual	(Sokol, Cerezo Davila, & Reinhart, 2017)
Karlsruhe (Germany)	~4,300	CityGML data, data from Institute for housing and environment (IWU), and district energy concept advisor	Energy planning and district energy analysis	City planners	Simulation in CityBEM using CityGML LOD data	None / Not found	5% to 10% yearly heating error and 18% to 80% yearly cooling error when compared with a TRNSYS model	(Murshed, Picard, & Koch, 2017)

Seville (Spain)	539	CAD building geometry from Cadastre, heights and openings from on-spot verifications	Energy efficiency measures for historic districts	City planners, urban planners	ArcMap and DesignBuilder	None / Not found	None / Not found	(Caro-Martinez & Sendra, 2018)
Gleisdorf (Austria)	1,945	Data supplied by utility services	Analysis of energy demand of building stock	Urban planners	GIS, IDA ICE	None / Not found	Mean deviation of -0.98% for annual heating and DHW demand between simulated and measured	(Nageler, et al., 2017)
St Gallen & Zernez (Switzerland)	1,845 and 120	OpenStreetMap, SwissTLM, swisstopo, MeteoSwiss, CMSAF SAHRAH, and Swiss Federal Statistical Office data	Study retrofit scenarios	City planners, policy makers	GIS	None / Not found	Average goodness of fit (R^2) or 0.6	(Buffat, Froemelt, Heeren, Raubal, & Hellweg, 2017)
Rotterdam (Netherlands)	~1,000	Geo-referenced measured yearly gas consumption records, CityGML model	Energy policy support, analysis of energy savings potential	Energy planners, local energy companies	GIS, CityGML, SimStadt platform together with statistical methods	City	5 to 25% deviation between simulated and measured gas consumption data	(Nouvel, et al., 2015)
Ludwigsburg & Karlsruhe (Germany)	57	CityGML model, typology libraries (e.g. IWU and Tabula)	Localization of energy savings potential and retrofitting priorities	Municipality, policy makers	CityGML with a quasi-static monthly energy balance algorithm	None / Not found	Overestimation of real heating demand by 21% and 7% in 2 case studies based on total simulated.	(Nouvel, Schulte, Eicket, Pietruschka, & Coors, 2013)

3.4. UBEM for Build-Level Recommendations

While municipal governments and policymakers are mostly concerned with stock-level analysis and finding "the right" policy levers to reduce carbon emissions, building owners' keen interest is how much a certain energy upgrade to their building or portfolio of buildings is going to save them. There is a sizable step between an archetype-level prediction and an individual building assessment. In the latter case an owner needs a somewhat customized recommendation that includes a range uncertainty and plausible return on investment (ROI). The Bayesian-calibrated models from **Figure 3-3b** offer such an evaluation. However, rather than simply utilizing building parameter templates calibrated on just a few representative buildings of the same archetype, one may go one step further by providing more detailed assessments of potential energy savings based on measured energy data for every building under evaluation.

With that goal in mind, UBEMs calibrated to the individual building level – or auto-calibrated models – have recently been developed. These UBEMs predict energy savings for individual buildings based on metered annual or monthly data for the buildings under study. For example, Nagpal et al. (2019) developed a technique using statistical surrogate modeling to significantly reduce computational cost and time compared with traditional calibration methods. The model was subsequently applied as a continuous energy performance planning system for a university campus in Cambridge, Massachusetts, to track historic energy data and explore potential scenarios for retrofits (Nagpal, Hanson, & Reinhart, 2019). Nagpal et al (2019) also introduced the concept of an ensemble model: a group of calibrated models for an individual building that each mimic the building's measured energy use using different combinations of input parameters. In the context of UBEMs, if energy savings measures are applied to an ensemble, a spread of possible (and potentially more accurate) savings emerges for each building. The outcomes are custom energy saving predictions for every building in a portfolio including an uncertainty analysis, as illustrated in **Figure 3-5**. These types of custom prediction can be used by a portfolio owner to identify buildings with the highest return on investment (ROI) for ECMs, and even further break down results into individual retrofit options (**Figure 3-6**). This approach can be applied in a variety of scenarios, including campus settings, a portfolio of nearby buildings, as well as geographically distributed buildings such as retail chains, etc. A similar approach was used by Garrison, New & Adams (2019) at the Oak Ridge National Laboratory using a supercomputer to automatically extract high-level building parameters and calibrate 178,377 buildings served by the Electric Power Board of Chattanooga, TN.

Other relevant works are listed in **Table 3-3**. Nutkiewicz, Yang, & Jain (2018) used convolutional neural networks (CNN) in combination with physics-based simulation to predict energy use in multiple spatial and temporal scales. In their study, predictions in smaller time-steps were found to have higher errors**.** Generally, granularity of the parameters and fidelity of the measured energy data used for UBEM calibration directly affects prediction accuracy, with finer prediction time-steps typically displaying greater uncertainties. This trend is also reflected in values defined by ASHRAE Guideline 14, where the stipulated calibration benchmarks for CVRSME and NMBE are 15% and 5% when calibrated against monthly data, but the acceptable range doubles to 30% and 10% for models calibrated hourly.

It is interesting to note that increasing geometry detail in an UBEM by using, for example, LiDAR data rather than extruded floor plans, has less impact than correctly dividing a building into representative thermal zones (Dogan, Reinhart, & Michalatos, 2016) (Smith, Bernhardt, & Jezyk, 2011). This occurs because zoning methods are a key factor affecting simulation results (Chen & Hong, 2018). Discretization of such thermal zones from complex, detailed building geometries can introduce complications which may be problematic. Using the aforementioned 2.5D building massing extruded based on shapefiles or low level-of-detail CityGML is therefore likely to be "good enough" even for UBEMs targeting building-level recommendation in many cases. In scenarios with complex zone definitions and specific zone requirements, more accurate, representative 3D geometries may be required.

While UBEMs calibrated at the building-level offer powerful first insights into potential energy savings for a building, it should be stressed that these results do not yet exhibit the predictive power of a manually constructed BEM. Auto-calibrated UBEMs' key role is thus to filter out buildings with high savings potential. Facilities team can then decide to initiate a more detailed study (or not).

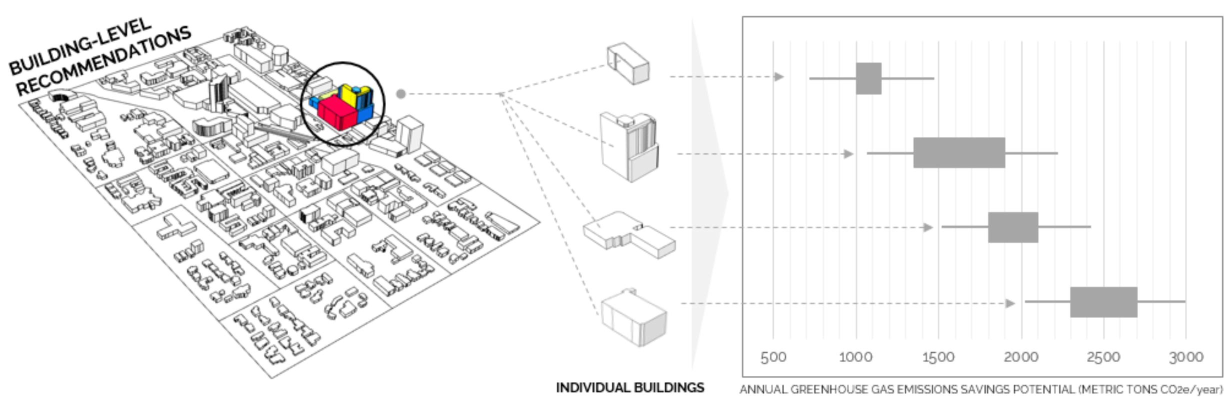


Figure 3-5. Example of using UBEMs to study potential greenhouse gas emissions savings potential for individual buildings in a portfolio, in a simulated area in Cook County, Illinois.

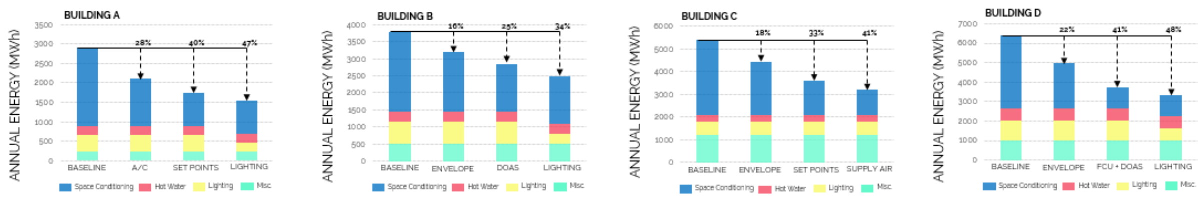


Figure 3-6. Example of using UBEMs to study potential energy efficiency retrofits for individual buildings in the same portfolio as in Figure 6 above.

3.4.1. The Minimum Viable UBEM for Building-Level Recommendations

The initial steps towards a building-level UBEM are similar to those for the other two application types. Building massing of the target buildings and surrounding urban infrastructure can be generated using the same type of public or private urban datasets. Auto-calibration takes significant computational effort for each building and requires building-by-building energy data. For buildings that are known to house multiple program types, the modeler may choose to generate separate geometries representing each program type and aggregate the results after simulating and calibrating each area separately. One common example is mixed-use buildings comprising a retail podium block and a residential tower block. For this type of analysis, it can be beneficial if an owner or facilities manager collects or has access to additional data pertaining to the buildings, such as construction assemblies, hours of operation, window-to-wall-ratios, etc. Much of this information should be available through building audits, as-built documentations, specification sheets, or even as-built level-of-detail 500 building information models (BIM). It is also noteworthy that the methodologies used for building-level UBEM simulations and calibrations generally require deeper technical know-how in machine learning and large data set manipulation than the earlier two UBEM use cases.

Table 3-3: Examples of building-level recommendation studies

City/Region	Number of buildings	Input Data and/or Source	Target Use / Application	Target Users	Modeling / Simulation Tool(s)	Calibration Level	Accuracy or Uncertainty	Source / Reference
Cambridge (USA)	3	Campus GIS data and measured energy data	Campus energy planning	Facility managers	Statistical surrogate model and physics-based model	Building	NMBE and CV lower than 5% for most cases with best model (electricity use)	(Nagpal, Mueller, Aijazi, & Reinhart, 2018)
California (USA)	22	GIS files from local municipal website, DOE reference buildings, CBECS	Multi-scale energy use predictions, design demand responses	Building owners, facility managers, energy planners	Sketchup, OpenStudio, and convolutional neural networks	Building	MAPE of 5.32%, 6.41% and 8.28% (training, development, and test sets) for monthly predictions	(Nutkiewicz, Yang, & Jain, 2018)
Chattanooga (USA)	178,377	Supplied utility data, physics-based EnergyPlus models from prior research	Power demand management, identify cost-effective ECMs	Grid operator, electric power board	Automated extraction of building parameters and calibration using supercomputer using EnergyPlus engine and OpenStudio	Building	None / Not found	(Sanyal, New, & Edwards, 2013; Garrison, New & Adams, 2019)
Aarhus (Denmark)	159	Geometry information from Danish Buildings and Dwellings Register, and datasets captured from the buildings	Predict district heating consumption	District energy planners, building owners	Reduced order resistance-capacitance model	Building	CVRMSE of 5.58% and NMBE of -1.39% for prediction	(Hedegaard, Kristensen, Pedersen, Brun, & Petersen, 2019)
Aarhus (Denmark)	50 training, 100 test	Data from the Danish Buildings and Dwellings Register and the local district heating supplier	Prediction and validation purposes	District energy planners, building owners	Physics-based model with statistical techniques	Archetype and Building	CVRSME of 7.8% and NMBE of 2.9% for prediction	(Kristensen, Hedegaard, & Petersen, 2018)

3.5. UBEM for Buildings-to-Grid (B2G) Integration

Municipalities typically focus on jurisdiction-wide carbon emission reductions from buildings. Building owners care about annual energy savings and ROI when exploring different energy retrofit measures. By aligning these two interest groups, UBEMs can help to significantly lower overall building loads profiles. However, for deep demand-side reductions to catalyse and bring about net societal and environmental benefits as well, building stock interventions need to be coordinated with supply-side planning such as distributed energy resources (DERs). Utilities and their partners are therefore another critical user group for UBEMs.

In recent years, a push towards low-carbon power grids and the associated rise in renewable distributed energy resources (DERs) have fundamentally changed how the grid operates in many parts of the world. Local energy storage facilities have been deployed to enhance grid stability and new high-capacity transmission networks aim to reduce the impact of local weather (Morvaj, Lugaric, & Krajcar, 2011). Demand response, which was traditionally limited to use on only on a few occasions each year, has equally become a viable option for everyday use (Razmara, Taylor, Xu, & Cotana, 2017). In this context, many utilities, energy authorities, and building owners are recognizing the significant impact of buildings on the grid, as well as the merits of data-driven models for predictive and demand responsive controls. For example, the US General Services Administration (GSA) commissioned a study analysing the value of grid-integrated efficient buildings across their portfolio (Carmichael, Jungclasu, Keuhn, & Hydras, 2019). This study focused on the peak demand impact of efficiency measures, the cost-effectiveness of these measures, as well as the potential savings for the owner both now and in the future.

From a utility standpoint, buildings can be both controllable consumers and producers of energy (Shao, Pipattanasomporn, & Rahman, 2012) and they provide unique opportunities for building-to-grid (B2G) integration. For example, HVAC ramping can be used to smooth out much of the variability from renewable sources, especially across large systems (Goddard, Klose, & Backhaus, 2014). Using the thermal mass of the building or an associated storage tank, HVAC systems, hot water heaters, and other appliances can provide small time-scale adjustments in power consumption that create meaningful demand response potential (Pipattanasomporn, Kuzlu, & Rahman, 2012). Where infrastructure constraints limit development of DERs or additional building loads, B2G integration can defer costly transmission and distribution upgrades (Pavlak, Wallin, & Kordas, 2014) (Wang, Liu, & Guo, 2012). B2G integration can also be used to improve stability and reduce power generation needs on subsets of the grid (Shabshab, et al., 20119).

Despite the plethora of potential applications, energy supply models and UBEMs have not been sufficiently integrated to date. Instead, buildings are usually represented as simplified nodes on an aggregated basis to reduce the complexity of power grid models (Makhmalbaf, Fuller, Srivastava, Ciraci, & Daily, 2014). There are some exceptions where physics-based modeling at the urban scale haven been used for demand response purposes. Yin et al. (2016) used EnergyPlus and statistical regression methods to design a demand response framework and study the associated load-shedding potential of HVAC systems in residential and commercial buildings. Another study (Yin, Kilicote, & Piette, 2016) developed an automated method to calibrate a model developed in EnergyPlus, after which space and conditioning loads were evaluated together with demand response strategies aimed at reducing peak demand. Mirakhorli & Dong (2018) introduced a model predictive control for residential buildings connected to the grid to integrate occupancy behaviour, building energy use, and electricity supply cost for price-based load control. However, it is noted that none of these studies integrated physics-based UBEM with grid modeling in full scale.

A contributing reason for the somewhat timid adoption of UBEMs by utilities may be that they have no direct jurisdiction over building load curves and those curves have historically been rather stable and undergoing constant, gradual increases. Nevertheless, the potential savings from building load curve manipulation to reduce grid operation costs can be enormous. In the US, 10% of power generation capacity is utilized solely to meet load demands for the top 5% of annual hours (approximately 400 hours a year), and 25% of the grid's distribution capacity is developed only to serve peak load for these same hours (Lightner & Pratt, 2004).

Upon first inspection, UBEMs, which output current and future hourly load profiles for buildings, seem to constitute an ideal complement to supply-side modules and support the integrated analysis shown in **Figure 3-7**, which illustrates an example of utilizing UBEMs to simulate energy usage of various building types and subsequently exploring options for load shedding. For example, a potential strategy to reduce peak load demand from residential buildings could leverage on-site photovoltaics (PV) and stipulate a higher temperature control setpoint. Electrification scenarios or price-based load control strategies could also be analysed using more integrated grid/building models to evaluate potential new chokepoints in the grid as overall load increases during operations. B2G integration can provide the coordination necessary to meet this load without substantially changing the capacity of the existing power system.

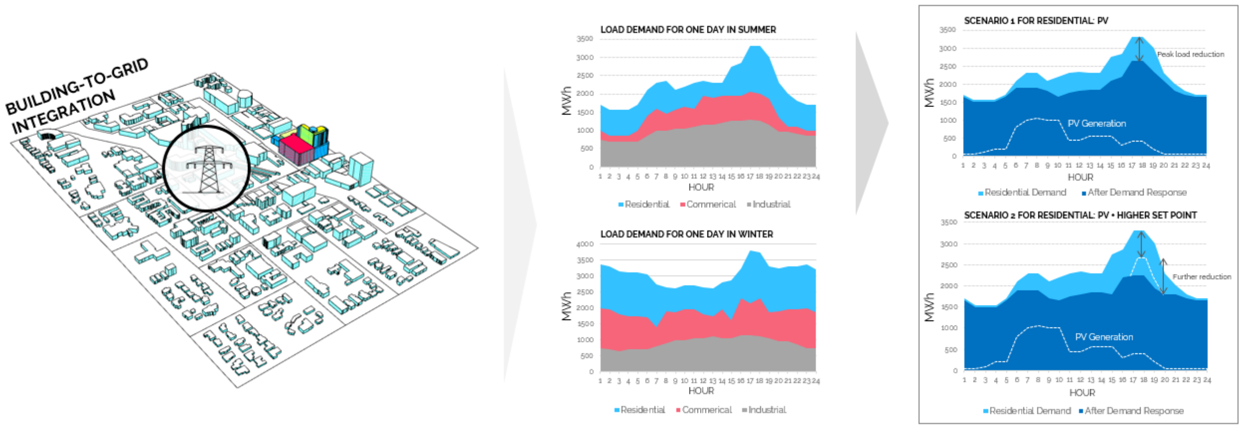


Figure 3-7. Example of using UBEMs to simulate energy use and study potential demand response scenarios in a simulated area in Cook County, Illinois.

However, while there are myriad ways to take advantage of B2G integration, it remains unclear how well UBEMs can currently predict building loads at the hourly (let alone sub-hourly) level. While the Bayesian and auto-calibration techniques mentioned in the previous sections have been validated at annual and monthly time steps, their capacity to predict higher resolution loads needs to be studied further.

3.5.1. The Minimum Viable UBEM for Buildings-to-Grid (B2G) Integration

While modelling workflows for the first three UBEM application types have been proposed and at least partially validated, reliably modeling hourly load curves remains an area of active fundamental research. Current UBEMs are generally able to accurately mimic time-of-day trends such that the electricity load curves in a city such as Boston peaks on hot summer weekday afternoons when electricity uses in commercial and residential buildings overlap. Such larger trends can thus be predicted and changes in load curves from large-scale PV deployment and / or thermostat readjustments can be approximated. However, even calibrated UBEMs tend to be based on static schedules for occupancy, equipment loads, etc. The result is a “city of robots” where large parts of society operate their equipment synchronously leading to exaggerated peak loads.

Improving UBEM fidelity to the hourly level requires several steps. First, hourly or sub-hourly metered data needs to be secured for a representative number of buildings, ideally in a comparably high-spatial resolution (apartment level) so that the root cause of load profile differences between buildings can be better understood. Given the imperative to protect individuals’ privacy, this data is hard to secure and needs to be handled delicately. Second, methods such as Bayesian calibration at the urban scale do not directly lend themselves to adjusting daily schedules that have significantly larger degrees of freedom. To overcome these obstacles, some studies have used unsupervised machine learning methods such as clustering of smart meter data to calculate baselines for residential loads (Sun, et al., 2019) (Zhang, Chen, Xu, & Black, 2016), identifying similar electricity demand profiles (McLoughlin, Duffy, & Conlon, 2015) (Rhodes, Cole, Upshaw, Edgar, & Webber, 2014), determining key variables influencing energy consumption (Deb & Lee, 2018) as well as enhancing predictions and forecasts (Barbour & Gonzalez, 2018).

Table 3-4: Examples of building-to-grid integration studies

City/Region	Number of buildings	Input Data and/or Source	Target Use / Application	Target Users	Modeling / Simulation Tool(s)	Calibration Level	Accuracy or Uncertainty	Source / Reference
USA	11	DOE reference buildings, metered data	Demand response, load shedding potential from HVAC systems	Facility managers, grid operators, utilities	EnergyPlus with statistical methods (regression)	None / Not found	Coefficients of determination (R^2) range between 0.39 to 0.91 overall. Fitted regression can predict DR potential with 80% to 90% accuracy for over 90% of data points.	(Yin, et al., 2016)
California (USA)	1	As-built architectural, mechanical, and control drawings, building operations and behavior data, and detailed equipment specifications and operations data	Demand response, peak load reduction	Facility managers, building operators	EnergyPlus	Building *(monthly and hourly)*	NMBE of 1.8% and 7.5% and CVRMSE of 12.5% and 5.7%. Monthly MBE within 10% for comparison between calibrated simulated and measured data.	(Yin, Kilicote, & Piette, 2016)
USA	1	Occupancy simulator from LBNL, prototype building from previous case study, data from local weather station	Interaction of building load controls with power grid	Building operators, grid operators, utilities	Model predictive control, RC thermal network model, and convex quadratic programming for optimization	None / Not found	None / Not found	(Dong, Li, Taha, & Gatsis, 2018)

3.6. Chapter Discussion

The previous sections presented a variety of UBEM use cases from urban planning and broad carbon reduction potential studies all the way down to fully integrated building-to-grid models that can support the transition of the built environment to carbon neutrality. As with any new technology, chances for widespread UBEM deployment depend on required effort levels, capacity to capture value, and how that value is distributed.

In the US, given the widespread availability of GIS shapefiles, TMY weather files, as well as building parameter templates for common building types, UBEMs for urban design and stock-level analysis could be widely applied in municipalities nationwide today. In the case of urban design, several Architecture, Engineering, and Construction (AEC) firms with a sustainability focus already have all the required know-how in-house. The incremental costs for building an UBEM for a new urban development may be in the order of tens up to hundreds of thousands of dollars, while potentially generating millions of dollars in direct savings for energy supply equipment. For municipal carbon reduction studies and energy management, the combined effort of a municipal GIS manager, who can link parcel IDs to building typology and manipulate GIS files, together with a sustainability consultant, who has sufficient knowledge of local construction practices and can identify suitable building upgrades, suffices to build an uncalibrated stock-level UBEM. Again, the required costs may be in-line with comparable consulting studies that are routinely conducted and commissioned by cities. As one transitions from building stock models to more detailed archetype-level based analysis and calibration, the study costs rise since metered data for a subset of buildings and higher efforts are required, increasing approximate costs to the hundreds of thousands of dollars range. However, the nature of such studies is that they are likely to take place over multiple years with municipalities ideally using the calibrated UBEMs regularly to adopt different incentive approaches. This longer time-horizon makes them a better option for policy planning and studies. Another flavor of such UBEMs are 'live' models which are regularly updated and re-calibrated based on new data streams. These models have vast potential for value capture over many years.

For individually calibrated UBEMs, the effort level rises considerable due to the required access to metered energy data for many / all buildings in a building stock. The computational and data management efforts for calibration are also substantial, increasing the costs to hundreds of thousands of dollars for industrial and institutional campuses to millions of dollars for larger cities and towns. The potential value gains for this use case have to commensurate with this effort level, since the beneficiaries of such an analysis range from city planners to institutions engaged in multi-year campus-wide retrofitting exercises to thousands of home-owners who wish to evaluate their retrofitting options.

Integrated UBEM-grid models have the capacity to change national energy landscapes. The development of such workflows and tools is still in its infancy and the costs are difficult to predict now. However, the economic and global environmental value could be immense, with over 135 million residential units and more than 5 million commercial buildings in the U.S. alone. These buildings utilize approximately 40% of total US energy consumption and 70% of total US electricity consumption (The Alliance to Save Energy, 2018) (US EIA, 2019). Demand response strategies for the grid could result in billions of dollars saved in terms of reduced grid operation and energy costs (US DOE, 2020a), leading to savings not just for cities/municipalities, but potentially adding millions to companies' bottom-lines across vertical sectors.

Finally, these use cases are by no means independent and detached, and should not be viewed or utilized in silos. A modeler can further develop – in greater detail and fidelity – the UBEM for stock-level carbon reduction strategies to suit building-level recommendation purposes. In the same vein, other use cases can potentially be built on top of the UBEMs that require higher effort level, and are of higher value. For example, information or building templates for building-level UBEMs can be used to generate archetypes for simulations of wider regions / areas to carry out stock-level carbon reduction studies.

3.7. Chapter Summary

Research on different urban building energy model types has greatly intensified in recent years, leading to an ever-expanding set of tools and techniques to design, evaluate, and change the relationship between buildings and the larger energy infrastructure. This chapter provided a high-level overview of the potential roles that these different technologies may play going forward and which techniques are most appropriate for which application and user group. The proliferation of open data platforms, coupled with cities' increasing willingness to share data, serve as enablers for these technologies. As a result, forward-looking municipalities, companies, and building owners are well-positioned to be the first beneficiaries of these new techniques in the immediate future.

Chapter 4

UBEM.io: A Web-Based Framework to Rapidly Generate UBEMs for Carbon Reduction Technology Pathways

This chapter focuses on expanding use case two – stock-level carbon reduction strategies – through the development and validation of a web-based UBEM workflow – UBEM.IO. The workflow is developed to help municipal policymakers worldwide generate rapid seed models, and iteratively run them to understand what specific mixes of building retrofitting upgrades are necessary to achieve their jurisdiction's carbon emission targets. UBEM.io automates key steps in the generation of UBEMs, widening access to these technologies to more cities.

Elements of this chapter have been published in the *Sustainable Cities and Society* journal:

Yu Qian Ang, Zachary Michael Berzolla, Samuel Letellier-Duchesne, Violetta Jusiega, Christoph F. Reinhart (2021). UBEM.io: A framework to rapidly generate urban building energy models for carbon reduction technology pathways.
https://doi.org/10.1016/j.scs.2021.103534

UBEM.io was a Finalist in the *Energy Category* for Fast Company's World Changing Ideas 2021.

4. UBEM.io

Policymakers are struggling to understand what specific mixes of building retrofitting upgrades are necessary to achieve carbon emission targets, but the use of UBEM tools requires hard-to-find individuals with training in multiple domains and significant setup time exacerbated by a lack of standardized building use and construction databases. To address these challenges, this chapter presents UBEM.io, a novel web-based framework to rapidly generate UBEMs in an automated and scalable fashion with clear handover points. UBEM.io is designed to help any city or municipality conduct low-cost, rapid energy and carbon emissions scenario studies. UBEM.io contributes to practice and research in multiple ways: automated generation of urban-scale building geometries based on widely available inputs; assignment of building simulation templates from a pre-populated library; matching of templates to individual buildings via archetypes; and visualization of simulation results for various carbon emissions reduction pathways. The framework was piloted in Evanston, IL (USA) to build an UBEM comprising of 1,363 buildings. It was then successfully deployed with representatives from eight cities: Braga (Portugal), Cairo (Egypt), Dublin (Ireland), Florianopolis (Brazil), Kiel (Germany), Middlebury, VT (USA), Montreal (Canada), and Singapore.

4.1. Existing Tools

The growing interest in UBEM has led to multiple research groups developing various UBEMs tools in recent years. One of the first UBEM tools is UMI (Reinhart et al., 2013) a plugin built on the Rhinoceros3D (McNeel, 2021) CAD backbone. UMI abstracts arbitrarily shaped building volumes into groups of simplified two-zone shoebox models using the so-called shoeboxer algorithm (Dogan & Reinhart, 2017). This process significantly reduces the computational resources and time needed for urban scale building energy modeling. CityBES (Hong, Chen, Lee, & Piette, 2016) uses the CityGML open data standard to represent 3D city models and runs the open-source EnergyPlus (US Department of Energy, 2020) simulations for various use cases, such as energy benchmarking and solar photovoltaic potential. URABANopt (Kontar, et al., 2020) was conceived as a software development kit (SDK) for community and urban district energy modeling, and similarly uses EnergyPlus and OpenStudio for building- and district-level energy simulations. Finally, CitySim (Vermeulen, Kampf, & Beckers, 2013) features its own solver, with computation of short- and long-wave radiation and a nodal thermal model to analyze building energy flows. Researchers have also developed custom-built solutions catering to individual case studies. For example, Cerezo et al. (Cerezo Davila, Reinhart, & Bemis, 2016) developed an UBEM workflow using Rhinoceros3D with custom Grasshopper definitions and custom C# scripts. They used the workflow to simulate citywide energy demand for over 80,000 buildings in Boston, MA, to support district-level interventions.

Most of the tools exist as standalone installers or software packages that will reside independently on users' computers, with a couple being web-based. Tools that utilize data-driven or top-down statistical methods such as regression techniques are excluded in this review, since these are not physics-based. While these approaches may be able to extrapolate urban energy use at scale, simulating building-level thermal balances at finer granularity or time-steps is typically out of reach. It should be noted that UBEM.io does not seek to replicate or replace any of the existing tools. Instead, it aims to act as an enabler and aggregator for a broader audience to start using any or all the existing UBEM tools. Most of the tools leverage the open-source EnergyPlus (US Department of Energy, 2020) whole-building simulation engine, the successor to DOE-2. EnergyPlus is primarily a console-based program that reads and writes text files and implements detailed building physics and thermal balance calculations for heat and mass transfer. UBEM.io does not implements its own energy simulation or heat transfer equations but rides on the simulation engine of the tool that it is interfacing with.

4.2. Methodology

As described above, the successful development and implementation of UBEMs requires three key roles – the city representative, the urban planner, and the energy modeler. The city representative (or sustainability champion) understands the carbon reduction target of the city or municipality. He / she has the authority to design / develop specific energy policy interventions for the city, as well as allocate the necessary resources to effect change (or at least has access to key decision makers who can do so). The urban planner or GIS manager manages and maintains spatial data pertaining to the city and has the technical know-how to update / organize the city's GIS files to develop a UBEM based on them. The building consultant or energy modeler can propose a variety of building energy retrofitting upgrades and put together building simulation templates to quantify their impact on individual buildings. UBEM.io brings the three parties together, assigning each a specific task within a seven-step process (**Figure 4-1**). The figure illustrates the overall flow of data and information along with screenshots of UBEM.io's graphical user interface (UI). The UI of UBEM.io is organized into sections which include an *urban model generator* (to generate UBEMs for different scenarios) and an *urban model visualizer* (to visualize simulation results for key metrics), with the possibility of adding additional modules in the future.

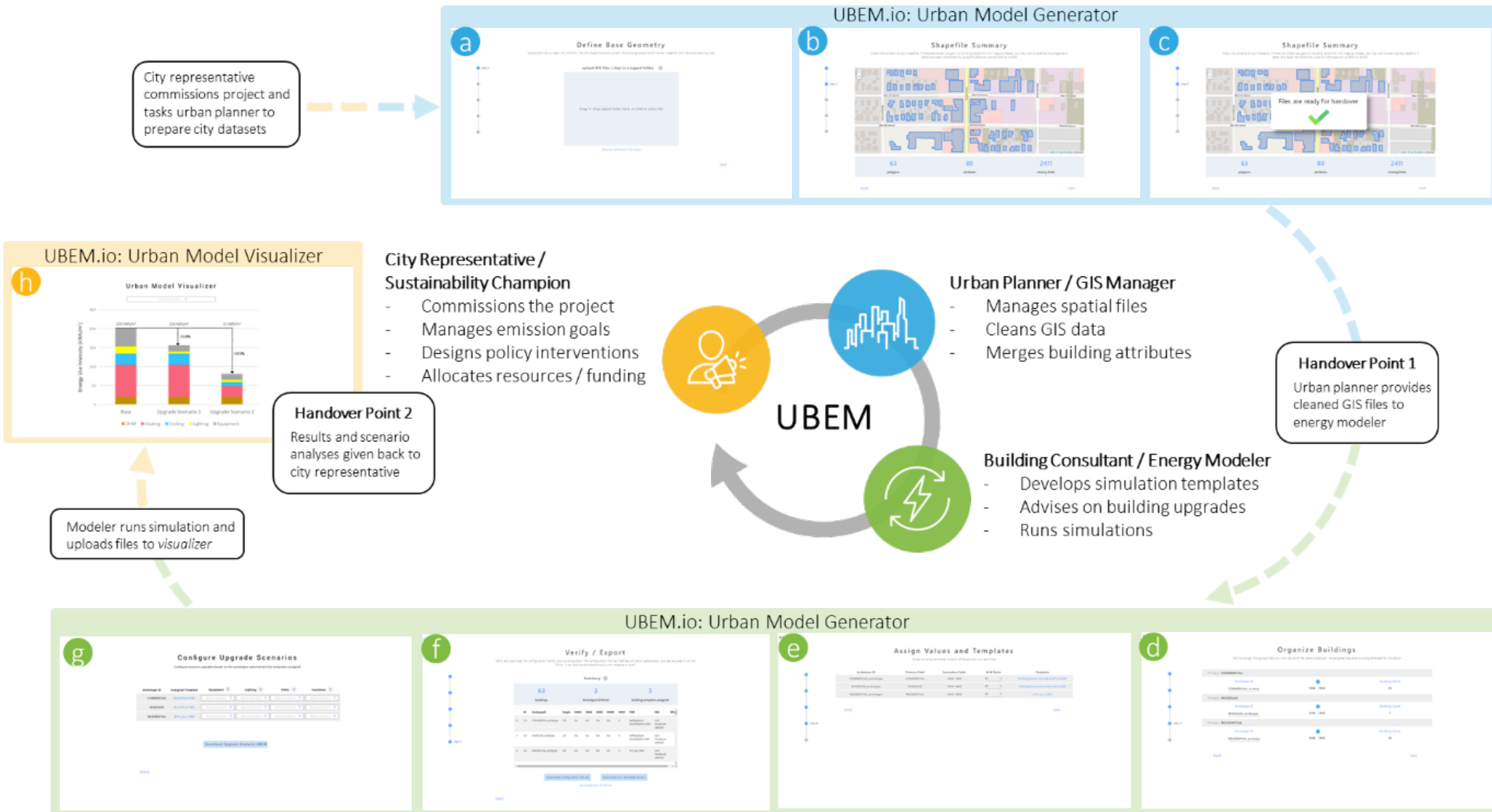


Figure 4-1. Overall driving motivation and methodological steps, including the frontend pages/steps for UBEM.io

An UBEM project typically commences when the city representative defines the scope and carbon reduction goals for the built environment and allocates funds for the GIS manager to prepare the city's data. The urban planner then organizes any spatial (GIS) files representing the region of interest, merges or adds required attributes, and processes the geometries. At this juncture, the urban planner can upload the GIS Shapefiles[2] representing building polygons onto UBEM.io (steps a and b in **Figure 4-1**). The file should contain building footprint polygons, height data for each polygon, as well as classification information to define the category or archetype (e.g., program/use type, building age). These complementary data can be obtained from various public sources such as property tax assessor data (Chen Y. , Hong, Luo, & Hooper, 2019). Currently, many cities and municipalities provide these data on public (open) data platforms to support planning and energy efficiency measures. GIS Shapefiles containing building footprints can also be extracted from sources such as OpenStreetMap or other open-source libraries (Boeing, 2017). If the shapefiles do not contain building heights, the data can be obtained using Light detection and ranging (LiDAR) data or digital surface models (DSM) which capture both the natural and artificial built environment features. Smaller cities may not provide these data on open platforms, but may be willing to share them upon request.

As a next step, the frontend makes several API calls to process the uploaded files, convert the attribute data to geographical data-frames, summarize key information, and project the results for verification (**Figure 4-1** step c). The planner can check if the building footprints and key information are accurate – i.e., whether critical information and attributes such as height and category information are missing. The end of Step c marks the handover point where the building consultant or energy modeler takes over the files.

In steps d to f, the energy modeler first selects key fields such as unique identifier (UID) and height, together with the attribute to categorize the building archetypes. If a UID field is unavailable in the original files, UBEM.io automatically generates and assigns an UID to each building footprint polygon in the backend. Next, the building stock in the file can be grouped and further segmented based on the energy modeler's understanding of the building stock. Each building archetype will be assigned a building template from the template library database. The templates are built in real-time as they are assigned. As the user selects the appropriate templates, buildings belonging to similar archetypes will automatically be assigned the same template, significantly reducing the time and effort necessary for manual assignment. In the final step of

[2] The first iteration of UBEM.io supports GIS Shapefiles, with additional support for other file formats such as GeoJSON, CityGML, and CityJSON in the development pipeline.

the *urban model generator*, a summary of the template assignment for each building footprint and other key parameters are presented in a tabular format in the frontend. After verifying this information, the energy modeler can download the completed UBEM to their computer to run the model in the energy simulation engine of their choice. Right now, UBEM.io supports the UMI file format with a planned expansion to other formats as needed.

Using the baseline UBEM generated by UBEM.io, the energy modeler can further define various upgrade or retrofit scenarios (step f) desired by the city or municipality based on budget, carbon reduction targets, or energy efficiency goals. These retrofitting measures may include upgrades to lighting, insulation, equipment, or HVAC system(s) etc. A bundle of UBEM files containing the baseline and upgrade scenarios can then be exported for simulations, to better understand impact and implications of these upgrades for policy development.

Finally, the energy modeler and city representative meet for a formal handover of the UBEM files with completed simulations to the city representative. During that meeting the UBEM files – including baseline and upgrade scenarios – should be uploaded onto UBEM.io for visualization using the *urban model visualizer*. The *urban model visualizer* allows users to quickly visualize UBEM simulations and energy results without having to format and organize them in spreadsheets or other charting software. The energy modeler should walk the city representative through the results and make technology-grounded recommendations. Going forward, these recommendations, along with the visualizations, enable the city representative to implement a custom energy policy for buildings within their jurisdiction.

4.3. Overall Technical Framework

The technical framework (**Figure 4-2**) for UBEM.io includes key modules for the frontend, backend, and template database. The backend implements the functionalities in the form of application programming interfaces (APIs). The frontend provides the user interface for user interaction. File input and output, such as uploads of GIS files and downloads of generated UBEMs, are handled via the frontend. The backend connects to a database which stores the template library with building components organized under specific schemas. Both the backend and frontend are containerized and packaged in separate Docker containers. This allows for resource isolation and packaging of dependencies in virtual container units, enabling the application to run in various locations under different conditions (e.g., locally or in a cloud service), which facilitates reproducibility, deployment, and troubleshooting. The entire web application is hosted on Amazon Web Service instances.

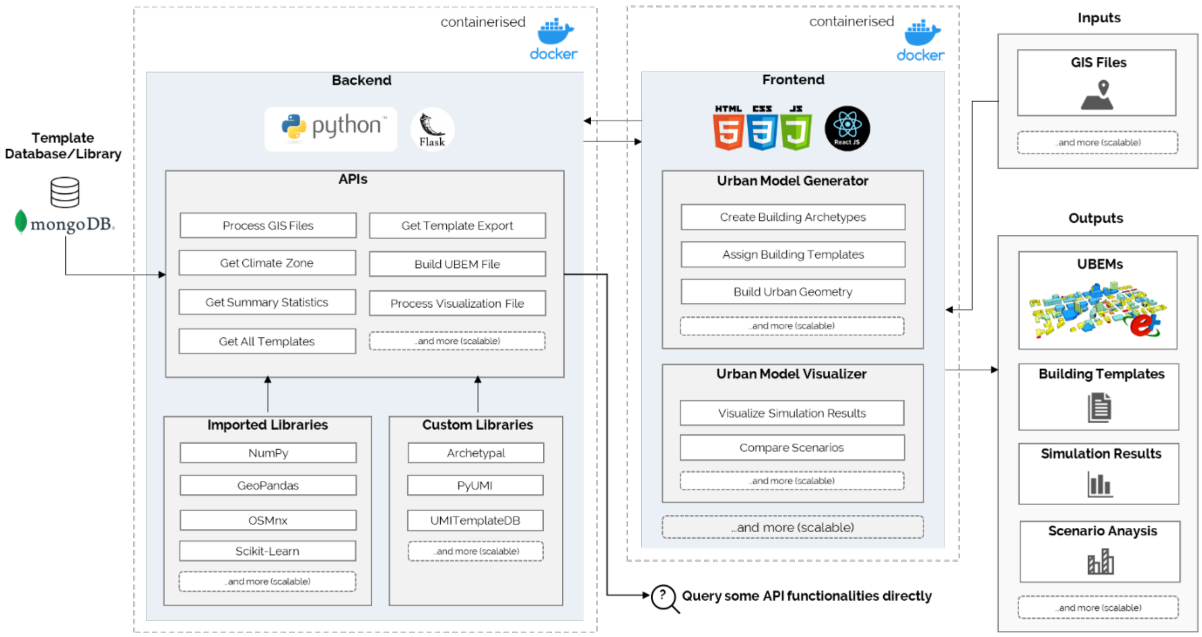


Figure 4-2. Overall technical framework and structure, including frontend, backend, and APIs for UBEM.io.

4.3.1. Backend and APIs

UBEM.io utilizes Flask (Pallets, 2010) for its backend. Flask is a lightweight Python-based Web Server Gateway Interface web framework that allows for flexibility and scalability. The ecosystem of available extensions and plugins provided by the development community makes adding functionalities easy. In the first iteration of UBEM.io, functionalities from external libraries such as GeoPandas (2021) (for working with geospatial datasets and dataframes), Scikit-Learn (2021) (for python-based machine learning predictive analysis), NumPy (2021) (an open-source numerical computation library supporting n-dimensional arrays), and OSMnx (Boeing, 2017) (for analysis of street networks) are imported and utilized in conjunction with custom APIs, functions, and libraries.

UBEM.io provides application programming interfaces (APIs) via its backend. APIs provides interactivity between multiple applications and expose certain functionalities to external users and developers. These APIs also define the requests or calls that can be made, the method to make these requests / calls, as well as the data formats and conventions to be used. UBEM.io abstracts some of the underlying UBEM functionalities, binding some API functionalities to the frontend while exposing others to users who prefer direct interactions with the backend. Some of UBEM.io's key APIs and their associated functionalities include:

- *Process GIS files*: loads GIS files in any coordinate reference system (CRS) and reprojects the files to the standard/common reference system i.e., the World Geodetic System (WGS) 84 for visualization and other manipulation purposes. It also stores the attributes of the GIS file in a flask session object to be passed across different API endpoints, as the user moves across various user interfaces (UI) in the frontend. It subsequently generates a GeoJSON (Internet Engineering Task Force (IETF), 2016) file which encodes the geographical and spatial data features.
- *Get climate zone*: Retrieves the most relevant climate zone using coordinates. The climate zones are defined by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) and the International Energy Conservation Code. These zone designations are intended to help architects, engineers, and builders identify the appropriate climate conditions for building design, performance simulations, etc.
- *Get summary statistics:* Processes and summarizes the key attributes in the GIS file, including number of complete polygons (representing building footprints), types of attributes/fields, missing attributes, etc., and send this information as a JSON dictionary to the frontend for downstream purposes.
- *Get all templates:* Retrieves all building simulation templates from the template database/library. The base template set for the US is developed based on the US Department of Energy (DOE) reference buildings (US Department of Energy, 2020), representing different building types – such as office, retail, hotel, apartment, and school in various climate zones. These provide description of the building properties, characteristics, and systems for whole building energy analysis and simulation purposes.
- *Get template export*: Creates template library with different templates based on the building archetypes in the urban region and the template assignment. The template library, comprising building simulation templates for each building archetype(s), will be exported along with the main UBEM file, downloadable via the frontend.
- *Build UBEM file:* Constructs the urban building geometry based on the building footprint geometries (polygons) in the GIS file and extrudes to 2.5D using the data in the 'height' attribute / field. Also assigns building simulation templates to each archetype (e.g., residential, commercial) based on user assignment in the frontend. UBEM.io automatically pulls the weather file from the weather station closest to the region of interest in the GIS file.

4.3.2. Template Database and Library

Non-geometric data for UBEM refers to building properties, construction make-up, occupancy schedules, and mechanical systems that must be assigned to each thermal zone within the building energy models. Although automatic generation of zones using CAD and design environments such as Revit, Rhinoceros3D, and SketchUp (and their associated plugins) is possible (Cerezo, Dogan, & Reinhart, 2014), the process of inputting building properties and characteristics is usually decoupled from geometry creation. This has led to commercial energy modeling software, such as DesignBuilder (DesignBuilder Software Ltd, 2020), providing pre-defined templates using default values to facilitate data entry (Donn, 2001). Some of these templates represent typical constructions while others incorporate considerations for code compliance. Building science practitioners typically assign these templates based on literature, prior knowledge, heuristic/prescriptive rules, procedural methods, and references such as guides published by professional bodies (e.g., ASHRAE Handbook of Fundamentals and International Organization of Standards (ISO) building codes, etc.).

To overcome challenges mentioned in the previous section such as the laborious process of defining and assigning templates, UBEM.io includes a template library database connected to the backend and frontend. This template library is hosted using MongoDB (2021), a source-available document-oriented NoSQL database for web applications. MongoDB utilizes a JSON-like document schema allowing developers and users to define the structure of the data. The JSON open-standard file format was selected due to its interoperability, as data is stored and transmitted in a human-readable text format comprising attributes of key-value pairs and array data structures. This schema allows for reproducibility and standardization across building templates.

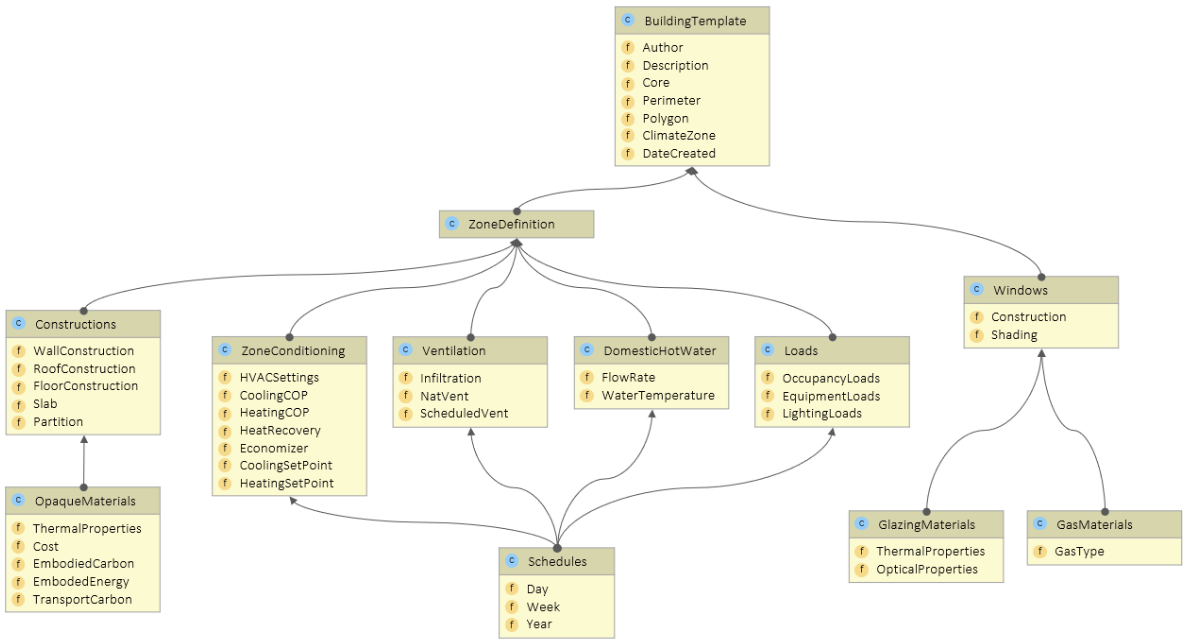


Figure 4-3. Building template structure in the template database library. 'c' indicates Python classes while 'f' denotes python functions.

Instead of storing individual simulation templates for each building type, the template database comprises individual modules serving as building blocks for different templates (Figure 4-3). These are encoded as Python classes and functions using object-oriented programming. Whenever a specific building template is required for a building archetype, UBEM.io's backend pulls the required modules to build the template in real-time. In the hierarchy shown in Figure 4-3, building templates are constructed from and comprise zone definitions, constructions, and windows. Each zone definition is made up of zone conditioning, ventilation, and internal load parameters, which can be adjusted with schedules of different granularities. Construction assemblies such as walls, roofs, and floors are built using material definitions, which contains specific thermal properties such as solar absorptance, specific heat, etc., as well as other parameters such as cost, embodied carbon, and embodied energy. Similarly, glazing units are constructed using glazing and gas material modules, through which thermal and optimal properties such as solar transmittance and reflectance can be defined.

One advantage of this modular system is the ability to generate template upgrades and create various custom scenarios for cities and municipalities. UBEM.io's backend API can pull wall assembles with lower u-values, as well as assign lower lighting power densities to zones, while keeping other template modules constant. The outcome is a set of automatically generated UBEMs representing various scenarios that the city / municipality might want to explore. This pipeline streamlines the entire workflow from technical details to policymaking, saving significant amounts of time and effort. Additionally, users are also able to customize building templates based on their building stock, and use those template libraries in the UBEMs generated by UBEM.io.

4.3.3. Prototype Pilot

To test how UBEM.io can be used to rapidly generate UBEMs and analyse urban energy use for cities and municipalities, a pilot case study was conducted using public data. An urban region of approximately 1.75km^2, comprising 1,363 buildings in the City of Evanston was used for the pilot study. The City of Evanston is part of Cook County, Illinois (United States), around 20 km north of Downtown Chicago. Evanston has a Climate Action and Resilience Plan (City of Evanston, 2019) aimed at carbon neutrality by 2050. For buildings, the city targets reducing building energy consumption 25% from 2005 levels by 2025 and reducing building energy consumption 35% by 2035. This pilot serves as a proof of concept to quickly understand the implications of various retrofit within their jurisdiction.

The process to develop the pilot case applies to most cities and municipalities around the world, with UBEM.io creating a synergistic linkage between the various people involved. This allows for a seamless transfer of data and process flow between the city representatives through to the GIS manager and the energy modeler.

In the pilot, the data pre-processing step is assumed to have been undertaken by an in-house GIS analyst with knowledge of spatial and / or geographical systems and software – it is noted that in practice, not every city / municipality will have this in-house personnel adept at performing these tasks. However, in most cases it is typically the responsibility of the GIS manager to maintain the building footprint files of their jurisdiction, and ensure they have sufficient, accurate data and are fit for purpose.

Four main datasets were used in the pilot. LiDAR data – point cloud data representing the region of interest – from Cook County were first obtained and extracted using the City of Evanston boundary shapefile. 100 points falling within the boundaries of each building footprint polygon were randomly sampled from the resultant point cloud, with the mean elevation of the 100 points taken as the height of the building. Next, property tax data were merged using a spatial join into each tax parcel, with the full data merged into the building footprint shapefile. The combined building footprint shapefile, which contains information for every building, was used in UBEM.io for the case study. Pre-processing was conducted using the open-source spatial software QGIS (QGIS.org, 2021). A segment of the GIS datasets is shown in **Figure 4-4** – i.e., how the various data sources are combined into a main building footprint file for the UBEM and loaded into UBEM.io. These steps are typically generalizable to most cities with minor changes based on data structures, contexts, and preferences.

Figure 4-4. Building footprint GIS file retrieved from the City of Evanston's open data platform (top left), opened in QGIS for processing (top centre), and loaded into UBEM.io (top right), as well as the spatial structure and datasets of the file (bottom).

A baseline UBEM representing the existing building stock in the region of interest was defined, together with two upgrade / retrofit scenarios for energy efficiency and carbon reduction. **Table 4-1** shows the model parameters for the base and upgrade scenarios. (Upgrade) scenario one represents a relatively lower-cost energy conservation measure (ECM) of upgrading the buildings in the region to energy efficient lighting and electrical appliances, while scenario two represents an additional upgrade of a gas-powered furnace to higher efficiency heat pumps.

Table 4-1: Summary of model parameters and assumptions in the base and upgrade scenarios.

	Base Case		Upgrade Scenario One		Upgrade Scenario Two	
	Residential	Commercial	Residential	Commercial	Residential	Commercial
Envelope Characteristics						
Average WWR	0.40	0.40	0.40	0.40	0.40	0.40
Wall U-value (W/m^2K)	0.60	0.50	0.60	0.50	0.60	0.50
Roof U-value (W/m^2K)	0.40	0.30	0.40	0.30	0.40	0.30
Window U-value (W/m^2K)	3.10	2.80	3.10	2.80	3.10	2.80
Glazing SHGC	0.83	0.83	0.83	0.83	0.83	0.83
Internal Loads						
Equipment (W/m^2)	8	10	5	8	5	8
Lighting (W/m^2)	12	15	4	7	4	7
Occupants (pp/m^2)	0.025	0.05	0.025	0.05	0.025	0.05
Mechanical Systems						
Heating Set-point (°C)	20	20	20	20	20	20
Cooling Set-point (°C)	24	24	24	24	24	24
Heating COP	0.9	0.9	0.9	0.9	5	5
Cooling COP	2.0	2.0	2.0	2.0	5	5
Infiltration (ACH)	0.15	0.15	0.15	0.15	0.15	0.15
Domestic Hot Water ($m^3/h/m^2$)	0.0005	0.0002	0.0005	0.0002	0.0005	0.0002

4.3.4. Further Validation and Application

After testing UBEM.io using datasets for Evanston, a three-day workshop with policymakers, city planners, academics, and researchers in eight cities / municipalities around the world was organized, to further test the UBEM.io framework in practice. These cities and municipalities include Braga (Portugal), Cairo (Egypt), Dublin (Ireland), Florianopolis (Brazil), Kiel (Germany), Middlebury, VT (USA), Montreal (Canada) and Singapore. The workshop involved graduate students from MIT with previous training in building energy modelling along with local academic partners and city representatives from all eight jurisdictions. In each of the cities / municipalities, city representatives provided carbon reduction objectives / questions and energy policy strategies for the built environment that can be addressed with UBEMs. The goals of the workshop were to raise awareness of UBEM technology among stakeholders worldwide as well as to test the ability of UBEM.io to support the development of carbon reduction technology pathways for buildings. In addition to developing questions and running simulations, the workshop covered technicalities of developing UBEMs, case studies of carbon reduction strategies, building simulation template development, GIS files clean-up and organization, as well as presentations by (and to) city representatives

4.4. Results

4.4.1. Evanston Prototype Pilot

The baseline UBEM shown in **Figure 4-5** is automatically generated by UBEM.io. UBEM.io simplifies the urban geometry construction process by automatically generating the urban building geometry, defining the site boundary, and extracting the street networks using OSMnx (Boeing, 2017). The template assignment process also simplifies the job of an energy modeler. For the pilot, the *urban model generator* builds the UBEM in the .umi[3] (Reinhart C. , Dogan, Jakubiec, Rakha, & Sang, 2013) format. Geometries for all 1,363 buildings are automatically constructed based on the building footprints in the GIS Shapefile provided by the city and the Chicago O'Hare International Airport weather file is automatically included.

The pilot UBEM simulated with building templates for single- and multi-family homes and standalone retail buildings in Climate Zone 5A. These templates are automatically assigned from UBEM.io's template database library to the individual buildings based on building type.

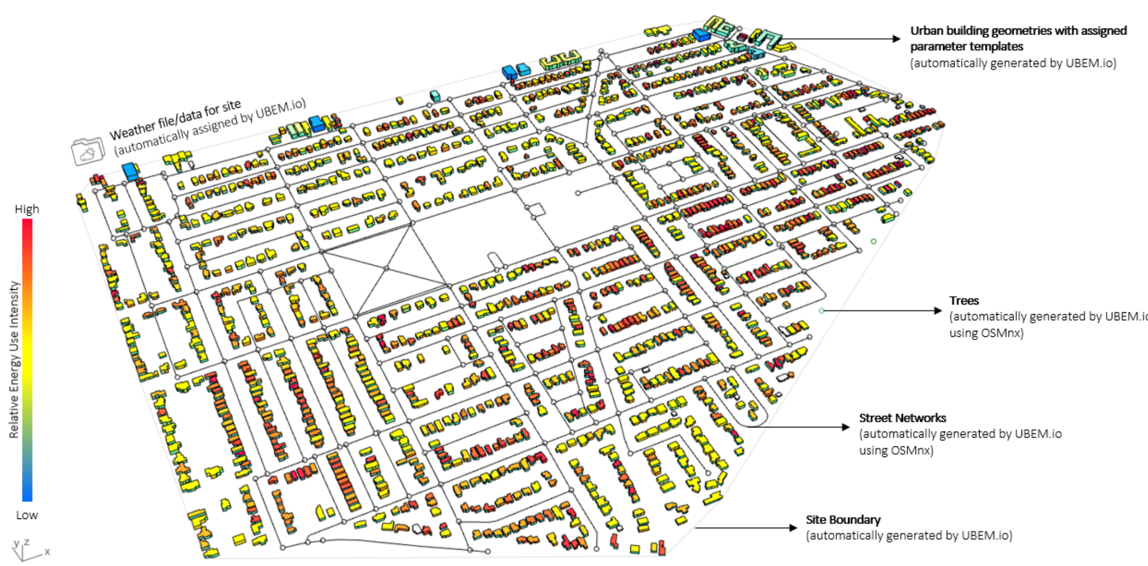


Figure 4-5. Base UBEM generated using UBEM.io's urban model generator after the simulation is completed.

[3] The urban modeling interface (UMI) is developed by the Massachusetts Institute of Technology. It rides on top of the Windows based non-uniform rational basis spline CAD modeler Rhinoceros as a plugin.

Figure 4-6 *s*hows that the results can be, automatically generated by the UBEM.io *urban model visualizer,* summarized for discussion with the city, and presented in various forms for further evaluation. Policymakers are typically interested in entire regions, neighbourhoods, or building types and categories instead of individual buildings. The results therefore must be succinct, clean, easy to interpret, and directly actionable.

In the case study, upgrade scenario one reduces the energy use intensity (EUI) in the region by 23%, while a deeper retrofit (scenario two) reduces the EUI by 60%. This corresponds to a 13% and 59% reduction of annual carbon dioxide emissions, respectively, using the specific fuel mix and emissions rate for Evanston (the RFC West subregion) for 2018 (United States Environment Protection Agency, 2018). Based on approximately 33,000 housing units in Evanston, adopting a phased retrofit/upgrade approach will ensure that the city meets its energy efficiency goal of 35% reduction for building energy consumption by 2035. Achieving carbon neutrality would require additional measures such as renewables (e.g., rooftop photovoltaics). These results and analyses are directly actionable and can guide the city planners and policy makers in determining the pace of retrofits and renewables deployment based on available resources and targeted timeframes.

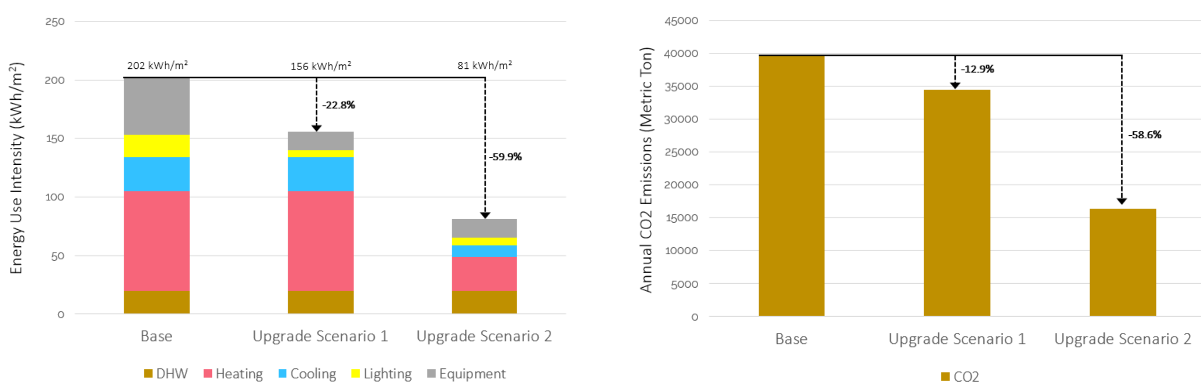


Figure 4-6a and 4-6b. Results for the base, upgrade scenario one, and upgrade scenario two in energy use intensity and CO_2 emissions.

Figure 4-7 compares the time required to build an UBEM of Evanston using UBEM.io versus the conventional approach. Typically, most energy modelers in consultancy teams are tasked to clean / process GIS files as well as to retrieve building heights – from LiDAR or other channels. Using UBEM.io, the authors assume that the city / municipality already has a set of GIS files as well as building heights data ready to be handed over to the energy modeler, who just has to validate or apply final touches[4]. The time taken to

[4] This assumption accounts for the time reduction for the pre-processing activities (grey) in Figure 4-7.

build UBEMs using conventional methods is consistent with academic literature (Nagpal & Reinhart, 2018) as well as informal validation with consultants. Time efficiency gains in the same ballparks can be expected for urban regions of comparable size as Evanston, with potentially even higher time reductions for larger municipalities.

It is to be noted that the results – and the time reduction in **Figure 4-7** especially the steps to clean the GIS data – refers to estimates pertaining to the project itself. This is work that the city GIS team should anyhow perform, and likely perform only once if proper building footprint files for the jurisdiction and their associated data are maintained. The process is contingent / incumbent on the GIS manager or urban planner from the city providing a usable, consistent set of files that can be loaded onto UBEM.io. Otherwise, there are several known issues that will affect the time needed to clean and process the building footprint data. Common issues include overlapping polygons, polygons with incorrect shapes and / or attributes, polygons with lines that are non-touching, duplicated polygons, polygons with duplicated attributes, etc – which will inevitably add more time to the project if not already resolve or correctly done.

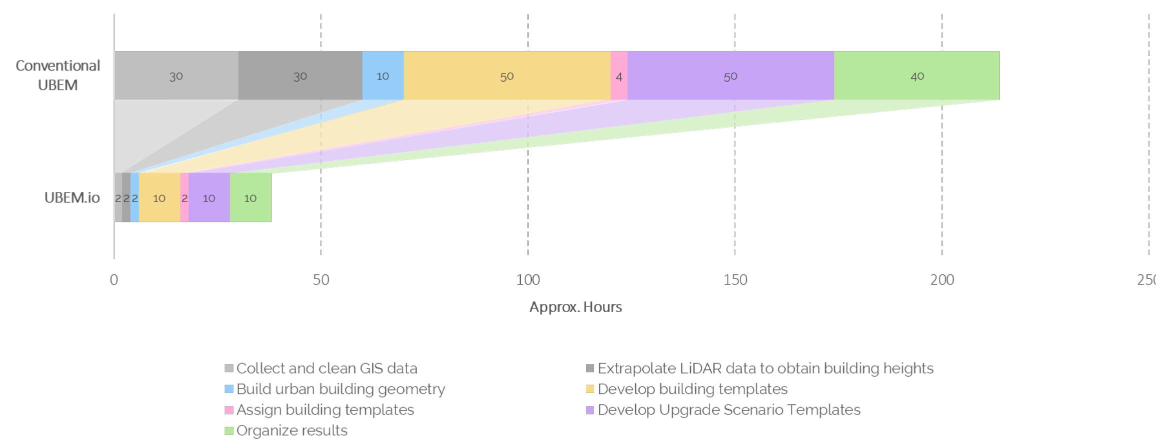


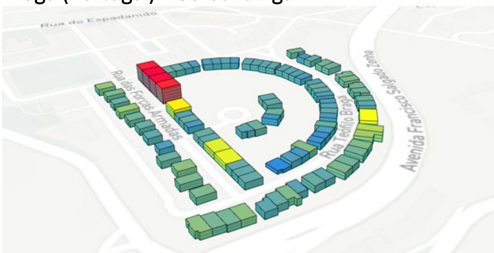
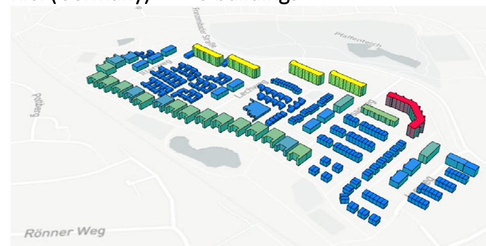
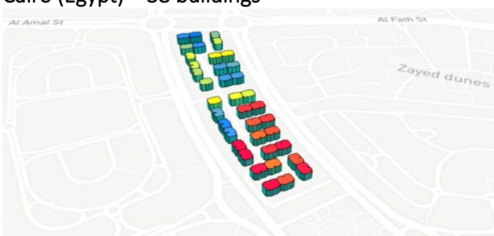
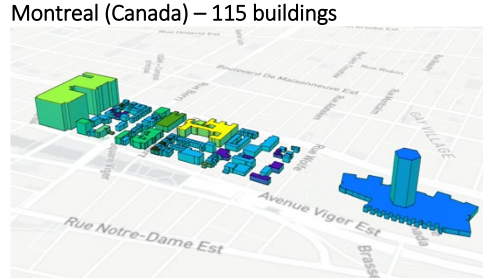
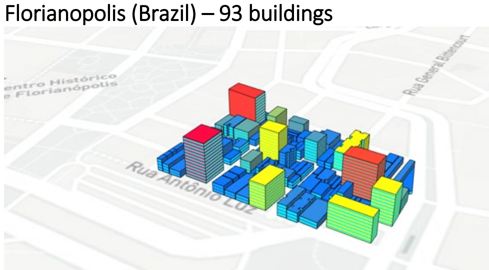
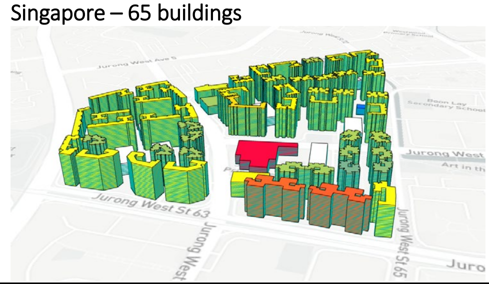
Figure 4-7. Estimated time required to for the case study region using conventional methods of developing UBEMs vs UBEM.io in the Evanston example. Overall, this leads to around a 46% reduction in time required.

4.4.2. Workshop Findings

Using UBEM.io, all eight city teams managed to complete model development, scenario studies, results analysis, and presentations (to the city representatives and policy decision makers) during the three days of the workshop. As explained above, the first day was largely spent scoping the project goals and the second half of the final day was spent on presentations (and Q&A), with approximately 1.5 days of work between them.

The people involved and final models are shown in **Table 4-2**. During the workshop, different team members assumed the role of the urban planner / GIS manager and energy analyst / modeler. The resulting UBEM models range from 38 buildings to 399 buildings in the regions of interest in each city, as defined by the city representatives. The building types are also diverse, from single- and multi-family homes (Middlebury) to dense high-rise public housing (Singapore). The findings will be further elaborated in the next chapter. Building on the success of the first workshop, future sessions with other cities and municipalities around the world have been planned.

Table 4-2: Summary of models and people involved

City/Municipality & Final UBEM	People Involved	City/Municipality & Final UBEM	People Involved
Braga (Portugal) – 95 buildings  	- Two architects from the municipality - One local faculty/professor - Two local post-doctoral researchers - One local PhD student	**Kiel (Germany) – 226 buildings**  	- Two architects from the municipality - One local industry representative - Two local post-doctoral researchers - One local PhD student
Cairo (Egypt) – 38 buildings  	- Two representatives from the United Nations (UN) Habitat local office - Executive director from the local authority - One local authority staff member	**Middlebury, VT (USA) – 93 buildings**  	- One local faculty/professor - Two local undergraduate students - Town manager - Town energy committee - Two PhD students
Dublin (Ireland) – 399 buildings  	- One head of climate action coordinator - One local PhD student	**Montreal (Canada) – 115 buildings**  	- Two architects from the municipality - One local faculty/professor - Two local post-doctoral researchers - One local PhD student
Florianopolis (Brazil) – 93 buildings  	- One representative from the local authority - Two local PhD students	**Singapore – 65 buildings**  	- Three representatives from the local authority - Three local undergraduate students

4.5. Chapter Discussion

The previous section demonstrates that the new simulation framework offered by UBEM.io can help municipalities overcome two barriers towards the development of technology pathways that helps them meet their carbon emission reduction goals for buildings: costs and finding a company to help them with the process.

The pilot application in Evanston shows that commonly available open data sets for a typical, mid-sized US city can be used to conduct an UBEM analysis in around two days. This leaves three days to discuss initial scope and present the results for policy development; meaning the full process only requires a week. Even when hiring an external consultant, the costs for such a project could lie in the US$10,000 to US$15,000 range (or even lower). If the same study were conducted by a practicing consultant without UBEM.io, the costs would likely be significantly times higher or more because of the specialty knowledge and custom, in-house workflows required. The latter cost is unattainable for all but the largest cities.

Given the aggressive city-level emissions reduction targets necessary to meet Paris Agreement goals, every municipality needs to leverage tools such as UBEM to identify the best technology pathways for their unique circumstances. UBEM.io greatly reduces the barriers to every community pursuing UBEMs. At $10,000, most municipalities can fund an UBEM study through operating budgets or philanthropic grants. Furthermore, the authors predict that the price of UBEM services will fall going forward as more consultants become familiar with the tools, especially for building stocks that are homogeneous and mostly residential, such as Evanston.

Without UBEM.io, a workshop where students and municipal representatives from eight cities around the world created fully functional UBEMs to guide policy decisions in three days would not have been possible. The pre-populated template library, simplified upgrade strategies, and visualization tools all made it possible for knowledgeable but not specially trained participants to rapidly create UBEMs in eight jurisdictions scattered around the planet. The success with this workshop suggests that the UBEM.io approach is scalable. Discussions with city representatives further revealed that the interest in and needs for building retrofitting upgrades vary significantly in various parts of the world. Some municipalities are almost exclusively focused on building retrofits whereas others face rapidly growing populations and the need to construct new housing units that are both efficient and affordable. These results from the workshop show that UBEM.io workflows are robust enough to meet the varied needs of jurisdictions and effectively influence city decisionmakers in crafting their emissions reduction technology pathways.

There are, however, several limitations to the UBEMs created using the approach documented. First, it was noted that the workflows in section 4.2 were based on an idealized process which in practice may be more complex and unstructured, especially across cities and municipalities of varying sizes and organisational structure. Usage of the UBEM.io framework and its tools are dependent on user inputs and archetype assignments. The tools and APIs assume that the users – such as the urban planner or GIS manager – has adequately pre-processed and cleaned the files containing the building footprints and the associated data to be fed into UBEM.io. This step, in many cases, can be the most time-consuming part of the process, and thus a possible improvement to UBEM.io is to identify pre-processing requirements for files from different regions, and further streamline and automate them. While the APIs can identify missing values or parameters, the framework relies on the user(s) to resolve broken or erroneous files and data. In this regard, the user(s) are required to possess a certain level of knowledge and technical capabilities.

Second, with the archetype approach, UBEM.io assumes a certain degree of generalization across the building template assignment and simulation. For example, building openings and fenestrations have a significant influence on thermal performance, and similar buildings – even on the same block – may sometimes differ in this factor. It should be noted that there are complementary simulation workflows available to extract window to wall ratios for street view images (Szcześniak, Ang, Letellier-Duchesne, & Reinhart, 2021), if available. Another area of data input uncertainty is material and/or construction assembly. While some countries have a built-up stock with standardized buildings categorized by construction period (Tabula, 2020) (Buckley, Mills, Reinhart, & Berzolla, 2021), certain regions may have buildings with properties that may differ. Using the archetype approach typically suffices for stock-level carbon reduction strategies, where policymakers and planners are generally more concerned with groups of buildings and their performance on a statistical distribution basis. However, users should be cognizant of the trade-offs between the level of detail and computational / simulation complexities in the various use cases, as described in **Table 3-1**.

Finally, while users can in theory customize building templates including construction assemblies and user schedules to correctly model a given building stock, detailed parameterization of HVAC systems such as specific dedicated outdoor air systems (DOAS), air handling units or fan coil units are currently not supported by the tool. Furthermore, the time to customize these templates adds significant complexity and cost to any UBEM study.

4.6. Chapter Summary

The knowledge of multiple domains and skillsets required to develop UBEMs can be prohibitive for many (especially small-to-mid-sized) cities and municipalities, which typically do not have sufficient resources to commit to emissions reduction planning despite their ambitious, well-meaning goals. This chapter presents UBEM.io, a new web-based framework to reduce the costs and streamline the process of developing UBEMs using commonly available datasets. UBEM.io is designed to help any city or municipality conduct energy and carbon emissions scenario studies using UBEMs by collaborating with an energy consultant who can initially advise city representative on what building retrofitting scenarios to explore, build an UBEM based on existing GIS and tax assessor datasets, conduct the simulation, and report results back to local decision makers all within a single work week. The framework was initially tested by the authors on Evanston, IL (USA), to build an UBEM of 1,363 buildings. It was then successfully applied in a workshop involving representatives from eight cities worldwide. The next chapter further describes the findings for these eight cities.

Chapter 5

Technology Pathways to Impact: Carbon Reduction Pathways for Buildings in Eight Cities

To further validate the effectiveness of UBEMs as a policymaking tool, this chapter presents the results of the collaboration with policymakers in eight cities worldwide, using UBEM.io to construct seed / minimum viable UBEMs, to identify each city's near- and long-term carbon emissions reduction targets for buildings.

5. Carbon Reduction Pathways for Buildings in Eight Cities

The study for this chapter was done in collaboration with representatives from eight cities and municipalities, as described in the previous chapter. For each city, a study framework that consists of individual pre-workshop meetings with the city representatives, a joint three-day remote workshop including goal setting and technical working sessions, and another set of individual debriefs was followed. The remote working sessions took place in January 2021. Representatives from the eight cities include local planning authorities, international organizations (such as the United Nations Habitat), and researchers.

During the morning of the first day, city representatives were invited to share their carbon reduction objectives along with specific questions pertaining to their local built environment context and interests. Eight seed urban building energy models (UBEM) were then developed with UBEM.io, each ranging in size from 38 to 399 buildings in neighborhoods for which building footprints, heights, program, and characteristics are available (**Figure 5-1**). Non-geometric building properties such as construction characteristics, building age, heating, ventilation, and air-conditioning system properties were compiled for each city before the workshop. For each seed UBEM, a baseline as well as shallow and deep retrofit scenarios were designed based on input from city decisionmakers. On-site electricity generation from PV was also predicted based on available rooftop area and climate. All results are expressed in term of energy use and carbon emissions reduction, taking current grid emissions factors into account. While the analysis is limited to the seed neighborhoods, the results are insightful in terms of emissions reductions across the entire city. Furthermore, city representatives were trained on how to expand their UBEMs after the workshop to other areas as needed.

The work in this chapter contributes to urban-scale energy research and policy in multiple ways. First, it was demonstrated how urban building energy modeling can be applied in conjunction with public datasets to inform “on-the-ground” carbon emissions reduction policy development. To the best of the author’s knowledge, this study – involving policymakers in eight countries and five continents – offers the first realistic assessment of the global carbon emissions reduction potential from building retrofits based on actual neighborhood data in various jurisdictions. This information dovetails with parallel efforts to decarbonize the transportation, industrial, and electricity sectors.

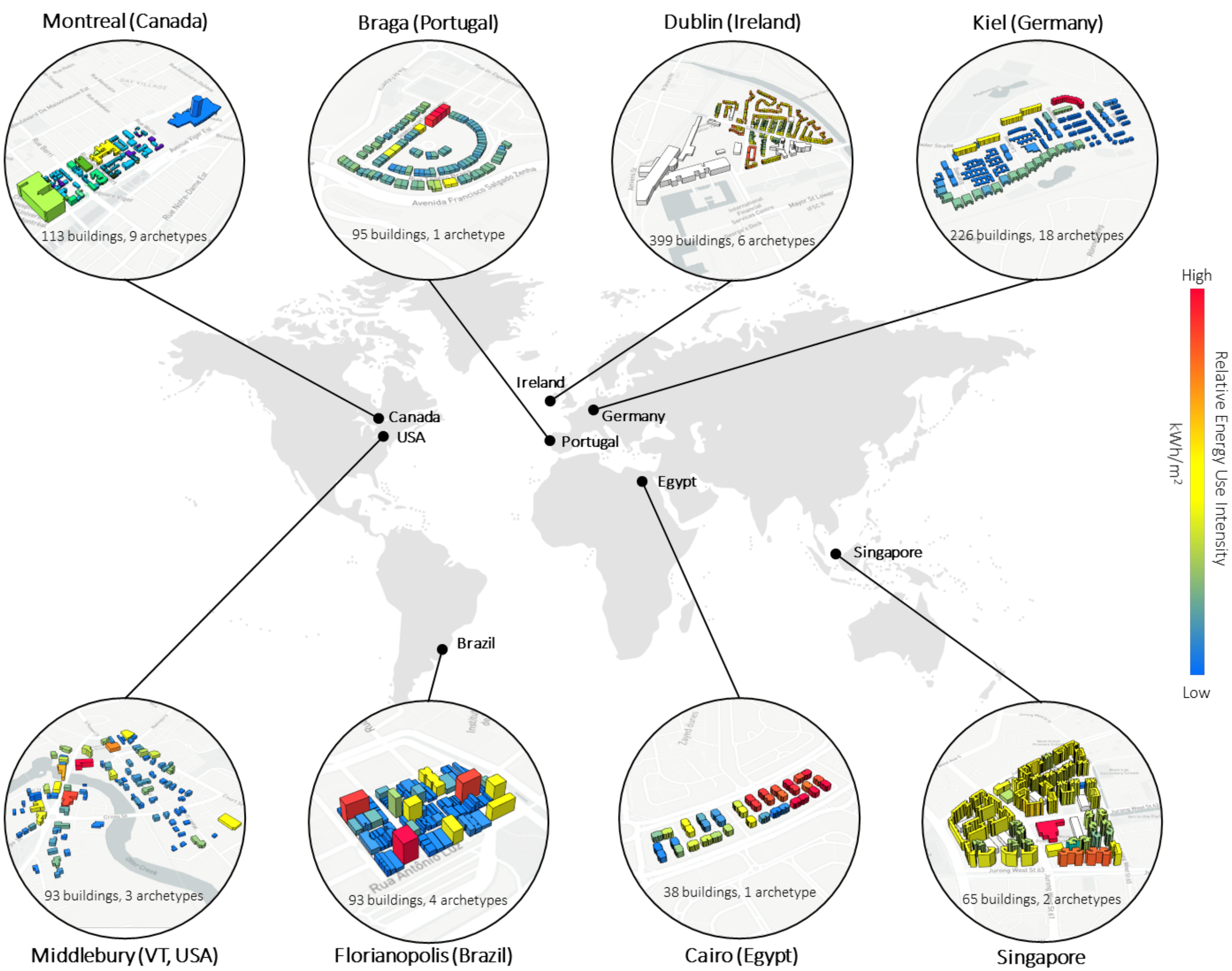


Figure 5-1: Baseline urban building energy models for the eight cities.

5.1. Methodology

5.1.1. Study Framework

A consistent study framework (**Figure 5-2**) was deployed across the eight cities. Specifically, representatives from the eight cities were first requested to identify and highlight policy objectives and carbon emissions reduction goals. Subsequently, they identified prototypical regions in their cities which represent the typical building stocks.

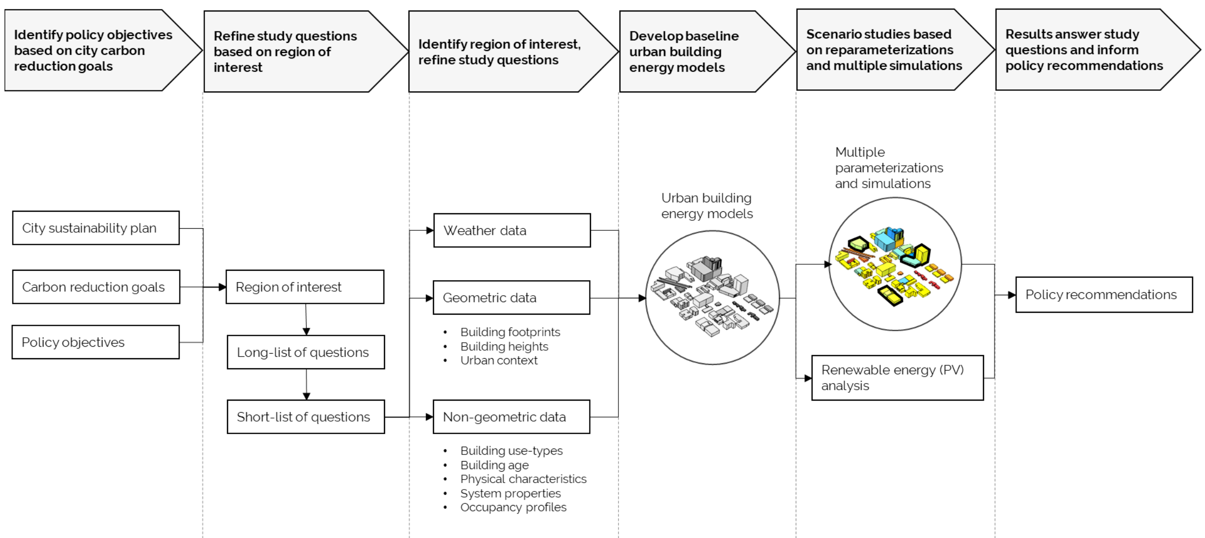


Figure 5-2: Study framework for eight cities

Next, geometric data such as geographical information system (GIS) files containing building footprints, street centerlines, as well as non-geometrical properties of the building stock were gathered. These include, but are not limited to, construction properties, window-to-wall ratios, mechanical systems type, and occupancy profiles. We retrieve weather data for each city from public repositories (Climate.OneBuilding.Org, 2021) (U.S. Department of Energy Building Technologies Office, 2021). These are utilized to construct the urban building geometries for each city, as well as to run the urban building energy and performance simulations. After multiple iterations for the baseline and retrofit scenarios, the results were to the city representatives for feedback. For the purposes of this study, some of the phased upgrades that cities proposed in the workshop were combined to present the overarching shallow and deep retrofits scenarios that the city representatives desired to explore.

5.1.2. Carbon Reduction Goals

Although the participating cities differ in size, climate, demographics, urban typologies, and building characteristics, most cities in our study have general carbon reduction strategies or climate action plans. These targets are broadly in line with the understanding set forth in the Paris Climate Agreement, with most plans having timelines including a near-term target and a longer-term goal aiming for carbon neutrality or net-zero emissions by 2050. However, only five out of the eight participating cities indicate that they have a detailed carbon inventory, and only four have carbon reduction plans specifically for the built environment (buildings).

Most participating cities in the study derive their carbon reduction goals and targets for buildings using a mix of in-house teams and government agencies with external consultants commissioned by the city. Only two cities indicated that they used data-driven methods (such as UBEM) to inform their targets.

To develop carbon reduction objectives, initial long lists of questions and potential technologies were proposed by the policy representatives based on the city's overall long-term sustainability plan and carbon reduction targets for the built environment. These are further refined into a selected short-lists of viable technological implementations aligning to their technology, economic, and socio-political needs. These include a list of potential energy efficiency retrofits and / or upgrades that the cities are considering incorporating in local energy policy levers, incentives programs, and/or regulations.

5.1.3. Urban Building Energy Models for Eight Cities

The baseline urban building energy models for all eight cities are constructed using UBEM.io, and the urban building energy modeling and building performance simulations were subsequently conducted using the Urban Modeling Interface (UMI) (Reinhart C. , Dogan, Jakubiec, Rakha, & Sang, 2013), a simulation and modeling plugin for the Rhinoceros3D computer aided design (CAD) environment. UMI utilizes the open-source EnergyPlus engine (United States Department of Energy, 2020) to simulate space conditioning (e.g., heating, cool, ventilation), equipment, and other loads, as well as their associated energy use. EnergyPlus is a whole building console-based energy modeling engine that implements detailed physics-based calculations for heat transfer, air, and other thermal metrics.

In every simulation a weather file is required to characterize the climate conditions in the local regions. These weather files are text files that define location-specific attributes such as longitude, latitude, elevation, design conditions, monthly average ground temperature, etc. for simulation purposes. Specific regional weather files for each of the cities that are freely available online [33] were used. To study impact of future climate for the city of Braga, the CCWeatherGen tool (Jentsch, Bahaj, & James, 2008) was used to generate a morphed weather file for 2080 that represents the potential future climate in the region.

Baseline UBEMs are reasonable empirical approximations of the building stock's current loads and energy use. The baseline models for the eight cities were developed by running simulations using the urban building geometries with building parameter templates, defined to match the physical characteristics of each archetype of interest in the region. These templates contain information on the buildings such as the physical properties, mechanical systems, and occupancy profiles. Archetypes are composite representations of buildings with relatively similar characteristics. Typical archetype categorizations include segmenting the urban building stock based on program / use (e.g., residential, commercial, institution), or building age. Baseline building template were defined for each city based on experience from previous work as well as discussions with municipal representatives. **Table 5-1** documents the assumptions.

Table 5-1: Descriptions and assumptions for baseline simulation models.

City	Domestic Hot Water Fuel & System	Heating Fuel & System	Electricity Emission Factor[5]	Fuel Emissions Factor[3,6]	Envelope Properties & Schedules Source
Singapore	Electric Resistance Boiler	N/A	0.4085	N/A	Adapted from the US Department of Energy Prototype Reference Buildings Zone 2A (U.S. Department of Energy, 2022)
Cairo (Egypt)	Electric Resistance Boiler	N/A	0.610	N/A	Adapted from (Cerezo, et al., 2017)
Florianopolis (Brazil)	Electric Resistance Boiler	N/A	0.09	N/A	Provided by academic partners from Universidade Federal de Santa Catarina
Braga (Portugal)	Natural Gas Boiler	Natural Gas Furnace	0.237	0.369	Adapted from (Monteiro, Pina, Cerezo, Reinhart, & Ferrao, 2017)
Kiel (Germany)	Natural Gas Boiler	Natural Gas Furnace	0.275	0.18	Based on TABULA (TABULA, 2017) Germany data provided by academic partners

[5] Emissions factors are provided by the city representatives

[6] Heating fuel varied by city and therefore the emissions factor for the fuel varies.

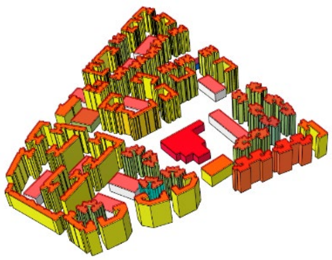
					from Christian-Albrecht University of Kiel
Dublin (Ireland)	Electric Resistance Boiler	Natural Gas Furnace	0.325	0.205	Adapted from (Buckley, Mills, Reinhart, & Berzolla, 2021)
Middlebury, VT (USA)	Natural Gas Boiler	Natural Gas Furnace	0.011	0.247	Adapted from the US Department of Energy Prototype Reference Buildings Zone 6A (U.S. Department of Energy, 2022)
Montreal (Canada)	Natural Gas Boiler	Electric Baseboard	0.0025	0.15	Adapted from the US Department of Energy Prototype Reference Buildings Zone 6A (U.S. Department of Energy, 2022)

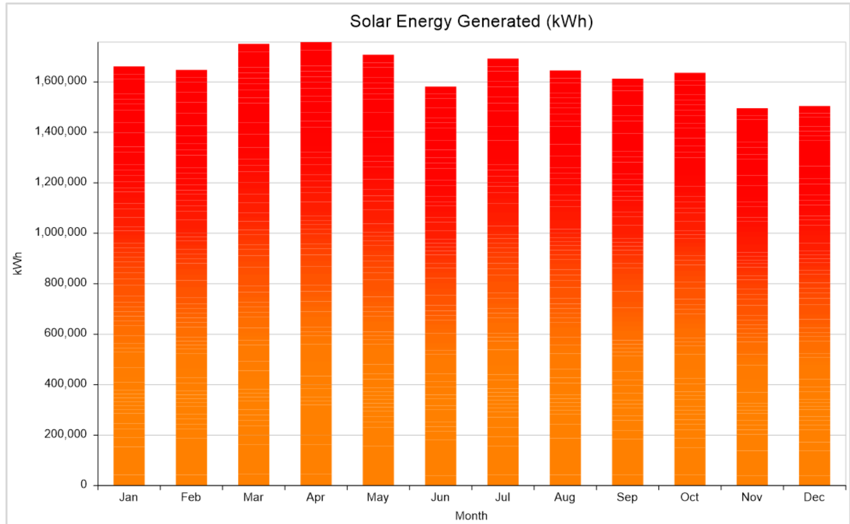
After establishing the baselines, retrofit and upgrade scenarios are designed based on the city representatives' preferred energy conservation measures and technologies.

5.1.4. Solar Energy Modeling and Simulation

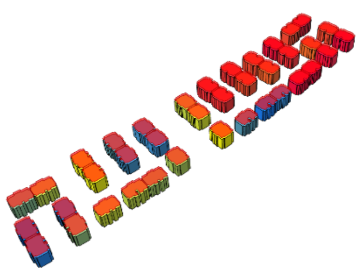
To simulate solar energy use, a custom visual programming script in the Rhinoceros CAD and Grasshopper visual programming environment was developed, using native components as well as components from ClimateStudio (Solemma, 2021), an environmental performance and analysis tool. Specifically, the script extrudes rooftop areas from the urban building geometries for each city, using the same GIS shapefiles. These areas are extruded as horizontal surfaces with the surface normal pointing in the direction of the z-axis. The surfaces are reasonable proxies for rooftop PV, where 100% of the rooftop surface is simulated in this study. In practice, however, full rooftop utilization is unlikely due to presence of clutter, mechanical and / or other systems or shading. Using these areas, together with the weather file and solar panel efficacies for each city, the annual potential electricity yield from rooftop PV is calculated for each region. Figure 5-2a to h shows the surfaces generated / extruded by our custom definition, as well as resulting monthly solar energy yield for each municipality.

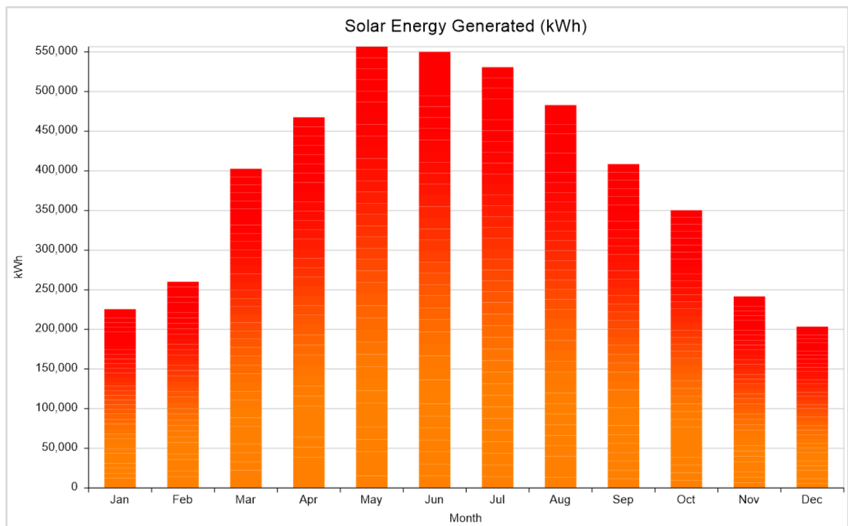
Singapore
PV Area: 98,472m^2



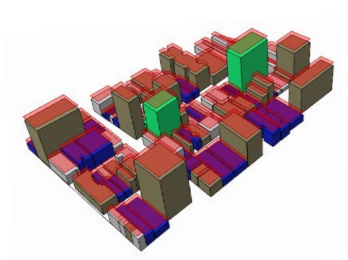


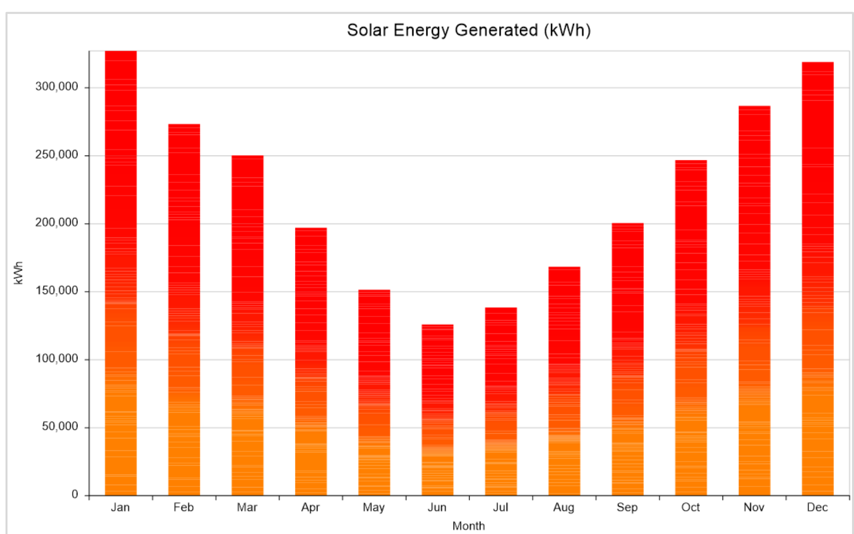
Cairo
PV Area: 19,480m^2



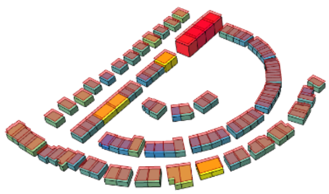


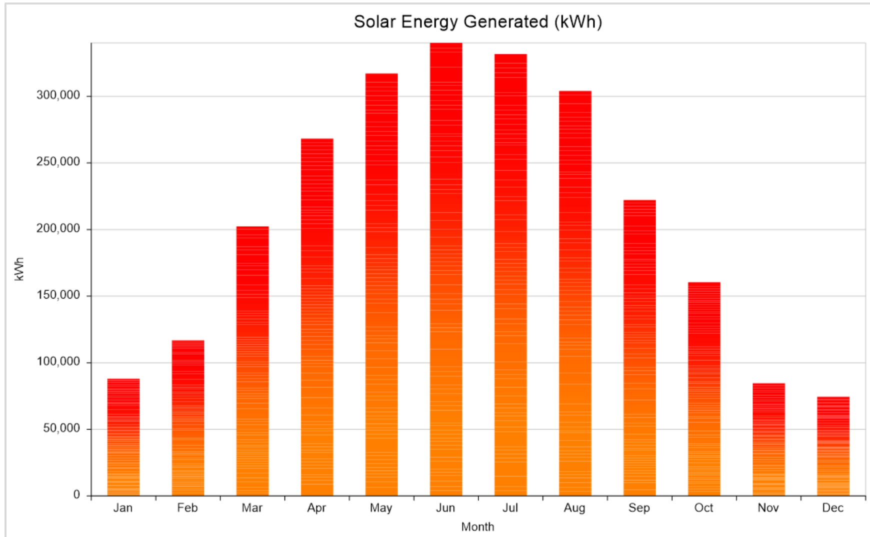
Florianopolis
PV Area: 14,406m^2



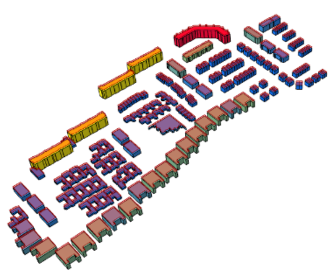


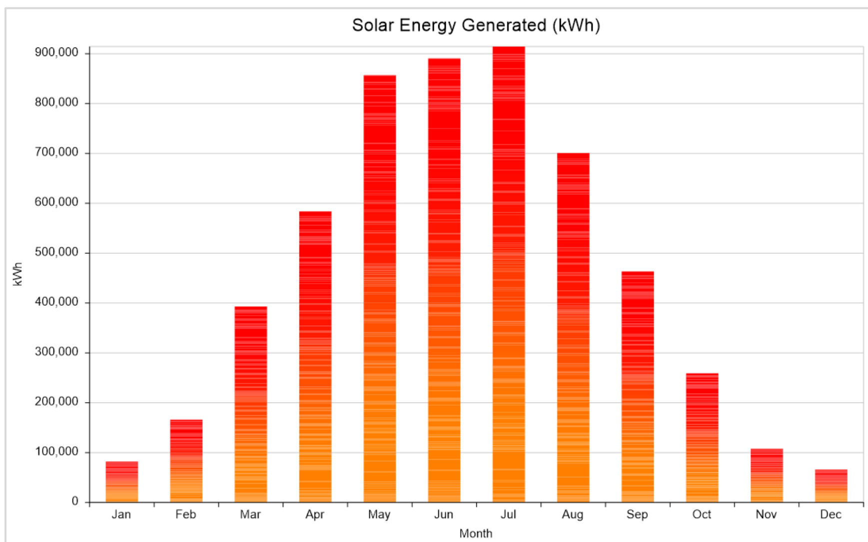
Braga (Portugal)
PV Area: 13,630m^2



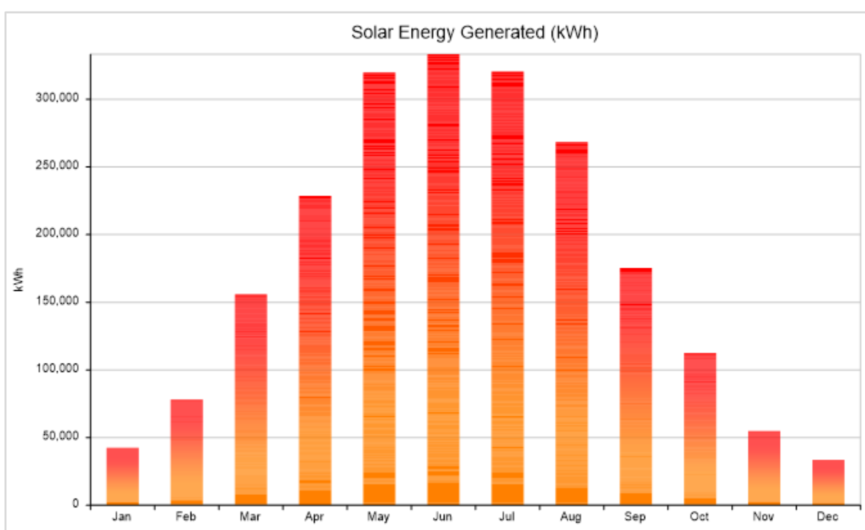


Kiel (Germany)
PV Area: 42,685m^2

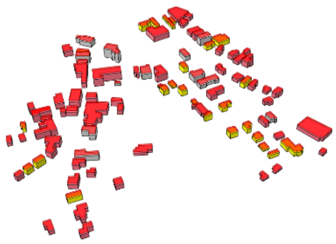


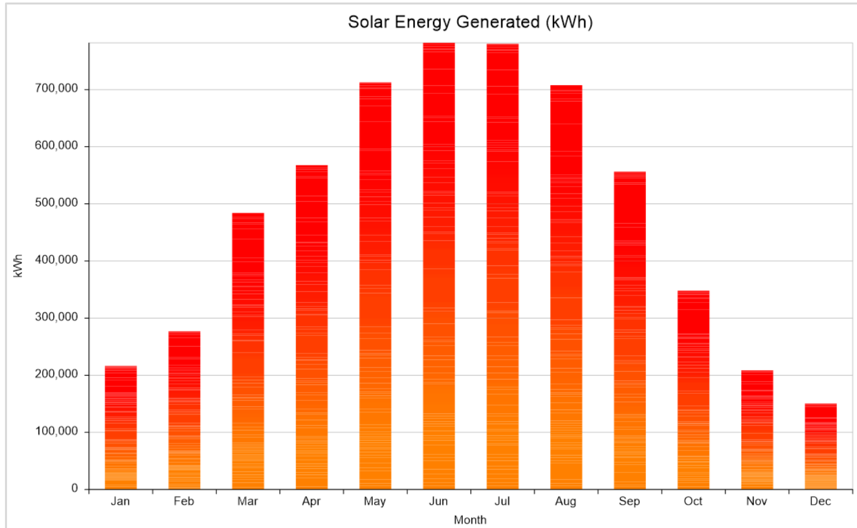


Dublin (Ireland)
PV Area: 19,106m^2

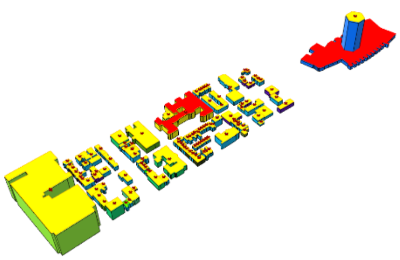


Middlebury, VT (USA)
PV Area: 34,010m^2





Montreal (Canada)
PV Area: 84,566m^2



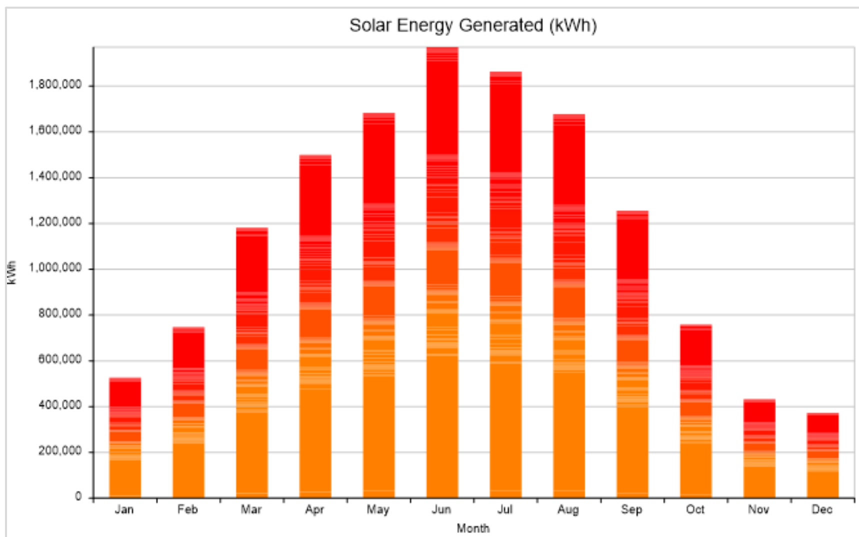


Figure 5-2a to h: Solar energy analysis for the eight cities and the annual solar energy yield

5.1.5. Baseline and Upgrade Scenarios

The eight cities studied represent a range of cultures and climate zones where most urbanites worldwide live. The following paragraphs present the priorities provided by participating city representatives, whose roles vary from city planners and sustainability directors to local NGOs. Based on these priorities, two retrofit upgrade scenarios were defined for each city, mostly corresponding to shallow (lower cost and / or easier to implement) and deeper (more expensive and / or harder to implement) retrofits (Table 5-1).

Singapore, situated near the equator, has a typical tropical climate with uniformly hot temperature and relative humidity. The mostly recent building stock is dominated by residential high-rises with moderately sized housing units, ubiquitous use of air conditioning, and good construction practices that manage to keep average household electricity use at the same level as temperate France (World Energy Council, 2012) (Energy Market Authority, 2021). The participating policymakers from Singapore's Urban Redevelopment Authority (URA) expressed interest in equipment load reductions, the impact of pandemic-related remote working patterns on load curves (Raman & Peng, 2021), as well as the energy-saving potential of district cooling systems (Temasek, 2021). To limit the scope of the investigation to the workshop goal of identifying carbon reduction pathways for buildings, our two upgrade scenarios for Singapore focus on the first and last area of interest.

Cairo has a subtropical desert climate with mild winters and hot, sunny summers. The city is cooling dominated, with increasing risks of severe heat waves due to climate change (Khalil, Ibrahim, Elgendy, & Makhlouf, 2019). The participating UN Habitat Egypt Office presented the twin goal of keeping the population healthy without excessive reliance on air-conditioning and a focus on widespread deployment of rooftop PV. The team did not provide a carbon reduction target. Based on previous experience from working in the region (Cerezo, et al., 2017), load reductions for shallow and enhanced air-conditioning and mechanical ventilation (ACMV) equipment for deep retrofits were recommended.

Florianopolis has a warm, humid subtropical climate with warm summers and mild winters. At the time of the workshop, the city did not have any carbon reduction goals for buildings but referred to country-wide targets of 43% and 100% by 2030 and 2050, respectively. Technologies of interest to the local team, consisting of municipal representatives and a nearby university, initially ranged from architectural interventions such as added exterior shading to reduced equipment loads as well as enhancements to

ACMV equipment. As the workshop progressed, the team increasingly concentrated on the latter two technology upgrades as they discovered the somewhat limited impact of exterior shading in retrofit projects.

In Braga, as in other Portuguese municipalities, a sizeable number of households suffer from energy poverty where indoor temperatures routinely reach uncomfortable levels, especially during the winter (Horta, et al., 2019) (Hernandez-Morales, 2021). Braga is further situated in a threshold climate (Santos, Forbes, & Moita, 2022), in which the use of air conditioning will increasingly become a necessity as summers get warmer. With building energy use already low, Braga's urban planning office is most concerned about the consequences of climate change along with energy affordability and health. For the "shallow" retrofit a future climate file was used to quantify future energy use if most households start using air conditioning to remain comfortable, and building envelopes were upgraded for the deep retrofit.

Kiel is one of Germany's major maritime centers, with a sub-oceanic climate influenced by currents from the Atlantic and the North Sea. Most homes in Kiel have no active cooling, and traditionally the emphasis has been placed on adding insulation to reduce heating energy use. The Director of the Kiel Authority for Environmental Protection accordingly expressed interest in added insulation and weatherization to reduce heating loads, as well as reducing energy use for domestic hot water. These measures are employed for the shallow retrofit. For the deep retrofit, electric heat pumps are added to electrify the remaining heating loads, a measure that is in line with ongoing German efforts to reduce the country's reliance on natural gas from Russia (Bimbaum & Mufson, 2022).

Dublin has a mild climate that is mostly heating dominated, with relatively comfortable summers and cold and humid winters. Due to the age and state of many buildings, thermal envelope upgrades represent one of the most effective retrofits (Buckley, Mills, Reinhart, & Berzolla, 2021) (Buckley, Mills, & Mee, 2018). Dublin contains a significant proportion of row houses, thus city targets coordinated retrofits in the form of weatherization upgrades for the shallow retrofit scenario, as well as added wall insulation and window replacements for the deep retrofits.

Middlebury is situated in the state of Vermont with warm, wet summers and freezing winters. The state has a largely decarbonized electric grid with high penetrations of renewables (United States Environmental Protection Agency, 2021). A key concern of participating representatives from the local energy committee and Middlebury College was hence to understand and quantify the potential of heat electrification and grid resilience. Technologically, these goals translate into air source heat pump adoption for space heating (shallow retrofit) along with envelope upgrades (deep retrofit).

Finally, Montreal enjoys a stable, decarbonized grid from hydropower. The city mainly seeks to reduce reliance on widely used electric resistive heating, due to it inefficiency, via natural gas furnaces, which are cheaper to operate but more carbon intensive for shallow retrofits. Ultimately, the city hopes to convince residents to invest into ground source heat pumps powered by clean electricity for both heating and domestic hot water use (deep retrofit). Given that natural gas furnaces, once in place, have a lifetime of 15+ years, these two approaches are not readily compatible with the city's 2050 target.

Table 5-2: Baseline model description and retrofit scenarios for the eight cities.

City	Carbon emissions reduction targets	Baseline	Shallow retrofit option	Deep retrofit option
Singapore	36% reduction from baseline by 2030 and 50% reduction by 2050 [7] (Singapore Ministry of Sustainability and the Environment, 2015)	65 buildings with 2 archetypes, primarily residential.	Upgraded baseline model with energy efficient lighting and appliances/equipment, as well as improved natural ventilation for commercial buildings.	Upgraded baseline model with district cooling system in addition to provisions in scenario one.
Cairo (Egypt)	No targets provided or found	38 buildings with 1 residential archetype	Upgraded baseline model with energy efficient lighting and appliances/equipment.	Upgraded baseline model with enhanced ACMV systems in addition to provisions in scenario one.
Florianopolis (Brazil)	43% reduction by 2030 and net-zero by 2050 *(adopted from Brazil's country-wide targets* (Governo Federal, 2020)*)* [8]	93 buildings with 4 archetypes, mixed.	Upgraded baseline model with energy efficient appliances/equipment.	Upgraded baseline model with enhanced ACMV systems in addition to provisions in scenario one.
Braga (Portugal)	40% reduction by 2030 and carbon neutrality by 2050 *(targets provided by city representatives)*	95 buildings with 1 residential archetype	Baseline model simulated with future 2080 climate and air conditioning.	Upgraded shallow retrofit model with improved insulation and shading devices.

[7] Adopted from Singapore's emission intensity goals
[8] Brazil's carbon neutrality target was originally set for year 2060 during our workshop, but the target was subsequently revised by the Brazilian government for 2050 instead.

Kiel (Germany)	95% reduction by 2050 (SCS Hohmeyer, 2017)	226 buildings, 14 archetypes, mixed.	Upgraded baseline model with improved insulation properties for the building stock.	Upgraded shallow retrofit model with heat pumps for space heating.
Dublin (Ireland)	40% reduction by 2030 (Rincon Consultants, Inc., 2020)	399 buildings with 6 archetypes, mixed.	Upgraded baseline model with better weatherization properties.	Upgraded shallow retrofit model with enhanced insulation and glazing.
Middlebury, VT (USA)	80% reduction by 2030 (Middlebury Select Board, 2021)	93 buildings with 3 archetypes, mixed.	Upgraded baseline model with heat pumps for space heating.	Upgraded shallow retrofit model with improved envelope.
Montreal (Canada)	55% reduction by 2030 and carbon neutrality by 2050 (City of Montreal, 2020)	115 buildings with 9 archetypes, mixed.	Baseline model with natural gas furnaces replacing resistive baseboard heating.	Upgraded baseline model with heat pumps for space heating.

5.2. Results

5.2.1. Energy Use Intensities

Predicted on-site baseline energy use intensities (EUI) range from under 89kWh/m^2 for Braga to 329kWh/m^2 for Middlebury (**Figure 5-3**). EUIs are mainly influenced by program type, climate, construction standards, mechanical systems, and urban typology. EUI subcategories for heating, cooling, lighting, domestic hot water, and equipment reflect these relationships – i.e., Cairo, Florianopolis, and Singapore are cooling demand dominated with no heating loads whereas Dublin, Kiel, Middlebury, and Montreal are heating-dominated.

In all cases except for Braga, EUIs fall for both shallow and deep retrofits. In Braga, where residents are expected to widely adopt AC units in residential construction due to a warming climate, the EUI for cooling goes up. The overall EUI increases by 24%, although heating demand decreases slightly due to milder winter temperatures. Retrofitting windows and shading has a marginal impact, with a simulated decrease in EUI of only 8%. In the other cities, shallow retrofits that address low hanging fruits like reducing plug and equipment loads lead to decreases in EUI between 13% (Dublin) to 36% (Cairo). Cairo has the largest energy efficiency gains from shallow retrofits since reducing internal loads from lighting and equipment has the dual advantage of also reducing cooling loads.

Deeper retrofits naturally lead to larger savings, from 32% in Middlebury to 66% in Kiel. In heating dominated climates, the largest energy efficiency gains tend be achieved by heat pumps even though these savings do not necessarily correspond to lowest operating costs due to the widespread availability of low-cost natural gas. Kiel, for example, has significant needs for space heating and domestic hot water, and heat pumps are effective in reducing overall energy use but pricy to operate. Dublin, like Kiel, has a high proportion of its EUI associated with heating and domestic hot water needs, but opted to reduce heating loads through weatherization and insulation. In Montreal, using natural gas instead of electricity has only a slight impact on EUI but raises emissions since the hydro-powered grid is so clean. In contrast, installing heat pumps shaves off 29% from the baseline EUI, primarily from heating and cooling needs.

5.2.2. Peak Loads

There is wide-spread consensus that decarbonizing the building sector will require the electrification of all heating systems while the electric grid will need to increasingly rely on renewable energy generation. To realize both strategies simultaneously, it is crucial to minimize the strain that buildings place on the grid. **Figure 5-4** accordingly shows the hourly annual electricity peak demand for each city for the three scenarios from **Table 5-2**. The date and time stamp for each peak is included in each column. Given that most policy representatives mentioned rooftop PV to reduce onsite carbon emission, a fourth column in **Figure 5-4** shows annual peaks for the deep retrofit scenario combined with deployment of PV across all building rooftops. The PV simulations assume 15% module efficiency for all cities and vary by available roof area and annual solar radiation.

In Cairo, Florianopolis, and Singapore the shallow retrofits reduce the annual peak ranging from 9% to 29%, while deep retrofits reduce the annual peak ranging from 39% to 55%. In Dublin, the heating is provided by natural gas in all scenarios, so the electric peak demand is driven purely by winter lighting and equipment loads and is only slightly reduced in the shallow scenario. In Cairo, Braga, Kiel, and Dublin, the peaks remain at around the same time of year and take place in the evening / morning for cooling / heating dominated climates. Given the limited availability of sunlight during those times, the deployment of PV does not affect the peak loads much except in Florianopolis where the Jan 23 5pm mid-summer peak is delayed to March 23 at 6pm and reduced by 20%.

In Montreal, switching to natural gas or heat pumps for space heating would reduce the peak by a factor of three. In Kiel and Middlebury, introducing electric heat pumps more than doubles the peaks, suggesting that substantial additional capacity would have to be added to the grid in these regions. In Middlebury the peak demand hour would further shift from the cooling-driven summer afternoon to winter mornings. However, if further combined with retrofitting measures, the peak in Middlebury could be reduced to even lower levels than the current baseline. Similarly, in Braga, widespread adoption on AC units will put significant strain on the grid that could be somewhat prevented through deep retrofitting measures. Our findings are consistent with studies (Langevin, et al., 2021) underlining the importance of buildings for grid demand management and energy policy planning. Peak load generating units – especially in the United States – typically rely on fossil fuels (U.S. Energy Information Administration, 2021), and can be costly to operate. Reducing utility peaks thus leads to fewer fossil fueled generation plants being brought online and reduces the need to build new distribution systems (U.S. Department of Energy, 2015).

Overall, our result show that the widespread use of PV will not significantly help utilities manage their electricity peaks. However, renewable energies will play a key role in reducing building-related carbon emissions.

5.2.3. Carbon Emissions and Pathways to Impact

Figure 5-5 shows annual carbon emissions for the baseline, shallow, and deep retrofit scenarios with and without deployment of PV across 100% of all rooftops. The underlying local emission factors for electricity and gas were provided by city representatives. Where applicable, the city's carbon reduction targets are also shown. Total carbon reductions for buildings range from 13% to 36% for shallow retrofits and 34% to 84% for deep retrofits across all eight municipalities.

Adding PV has the biggest relative impact in Florianopolis with final carbon emission reductions down 81% from baseline. As one would expect, the use of rooftop PV is most effective in reducing carbon emissions in low density neighborhoods and sunny climates where the proportion of electricity to gas use is high and the local grid is carbon intensive. Cairo and Florianopolis meet these criteria. PV has limited impact in Middlebury and Montreal which have the cleanest grid across the eight cities.

Municipalities with "modest" (or realistic) emission goals such as Singapore and Dublin can eventually meet their reduction goals based on the investigated technology upgrades in **Table 5-2**. Cities aiming for carbon neutrality are not going to realize those ambitions unless they pursue a combination of deeper retrofits together with off-site renewable energies such as solar, wind, or hydro as well as complete heat electrification: One upgrade conspicuously absent in most municipalities was heat pump hot water heaters. As seen in Figure 5-3, hot water contributes a substantial percentage to cities' energy use, yet few strategies were implemented to eliminate hot water emissions. In Middlebury and Montreal, for example, where the power grid is already "clean," the natural gas consumption for hot water heating leads to nearly all the remaining emissions in the deep retrofit scenario in Figure 5-5.

The potential pathways to impact can also be translated to frontier graphs as depicted in Figure 5-6, where the x-axis represents percentage of buildings retrofitted, and the dual y-axes showing the percentage of rooftop covered with PV as well as absolute PV capacity. Accordingly, the limit for 100% rooftop coverage is also drawn. Out of the eight cities, only Cairo, Kiel and Dublin have regions feasible to achieve their long-term carbon emissions goals shown in the orange intersection region.

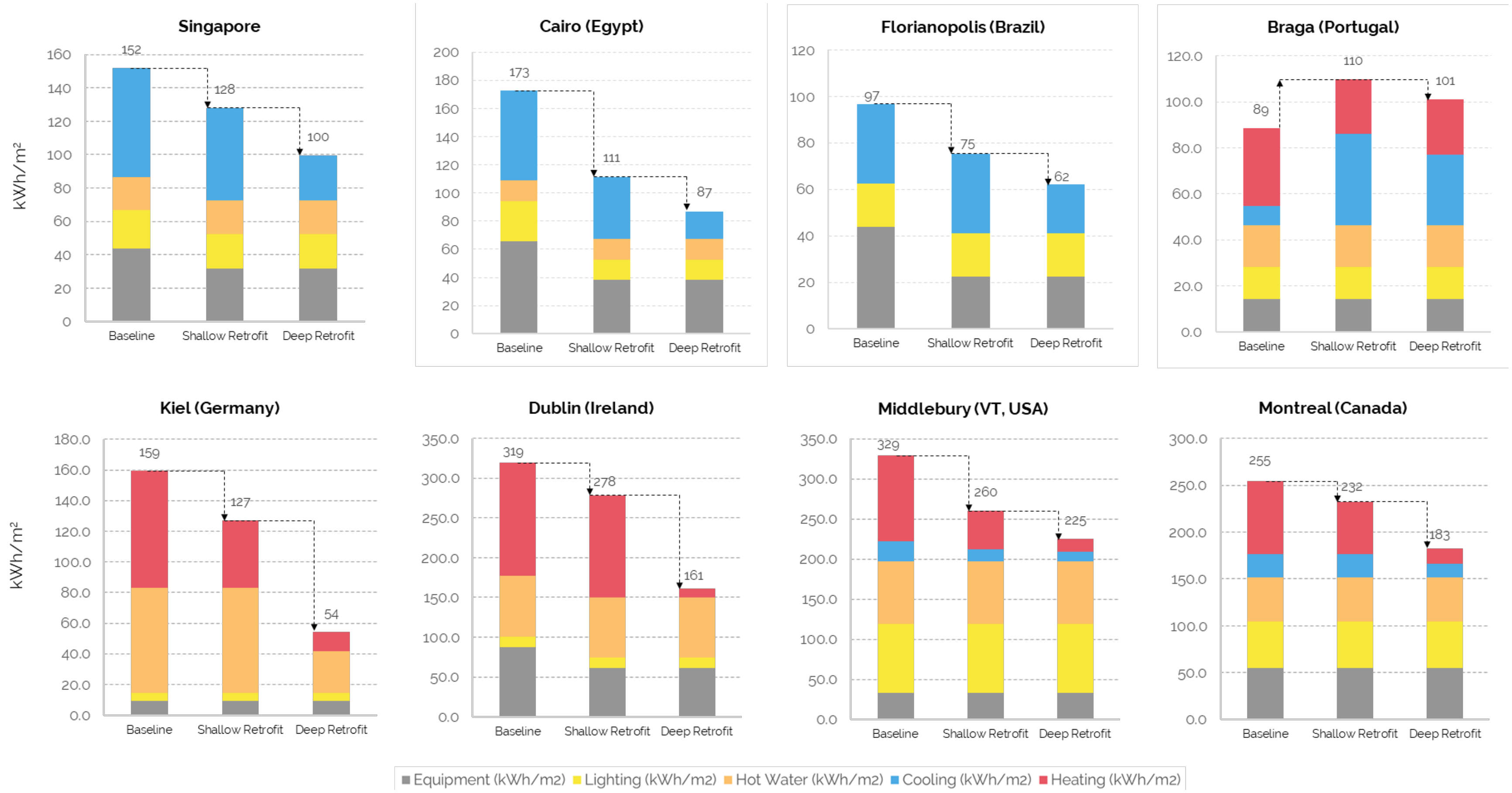


Figure 5-3: Energy Use Intensities for the baseline and retrofit scenarios for eight cities.

Figure 5-4: Annual electric peak for baseline, shallow and deep retrofit scenarios including 100% deployment of rooftop photovoltaics; The time stamp over each column marks the occurrence of the peak.

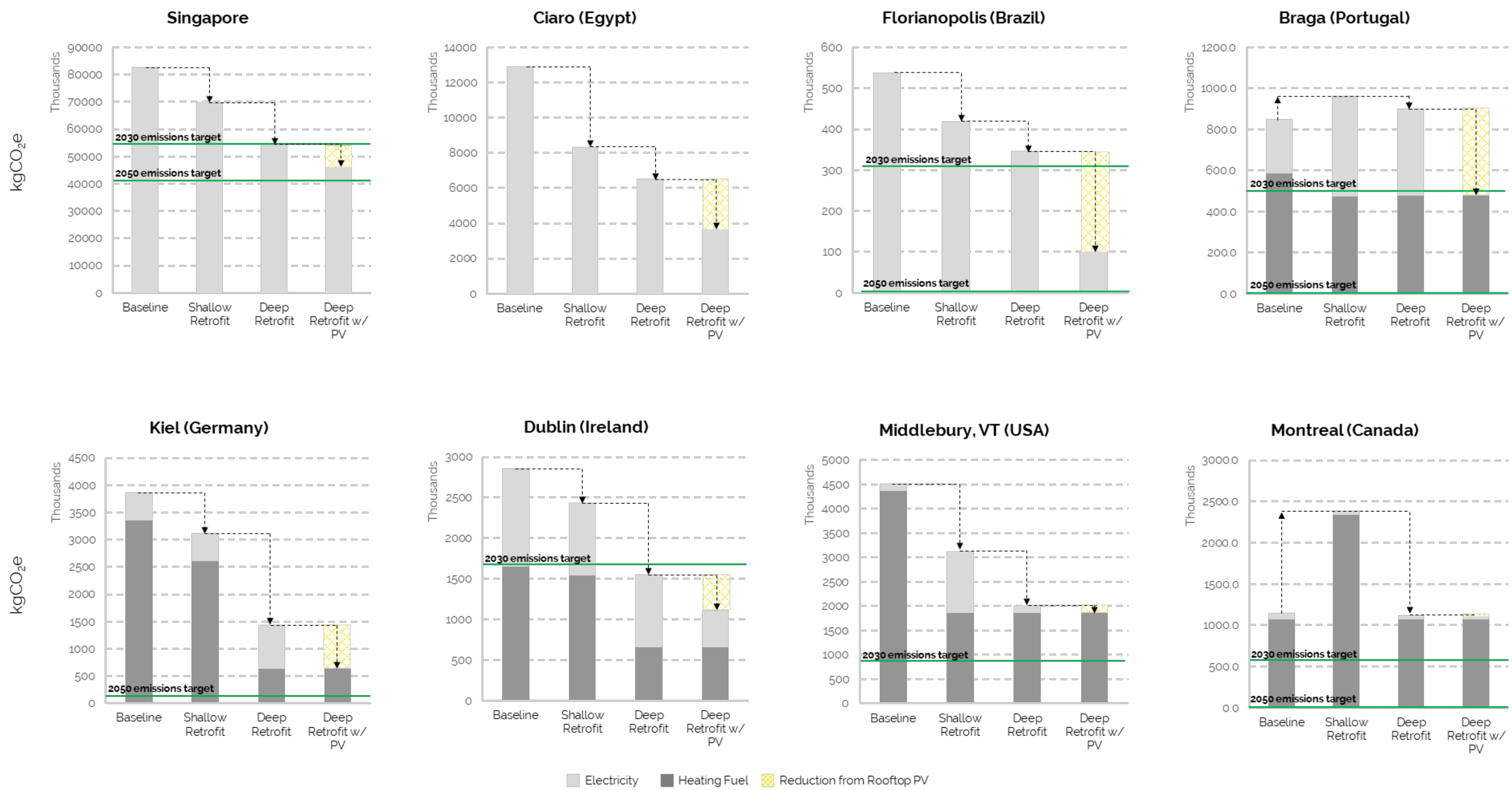


Figure 5.5: Annual carbon emissions for baseline, shallow and deep retrofit scenarios with and without 100% deployment of rooftop photovoltaics; Where applicable, carbon emission targets are shown in green

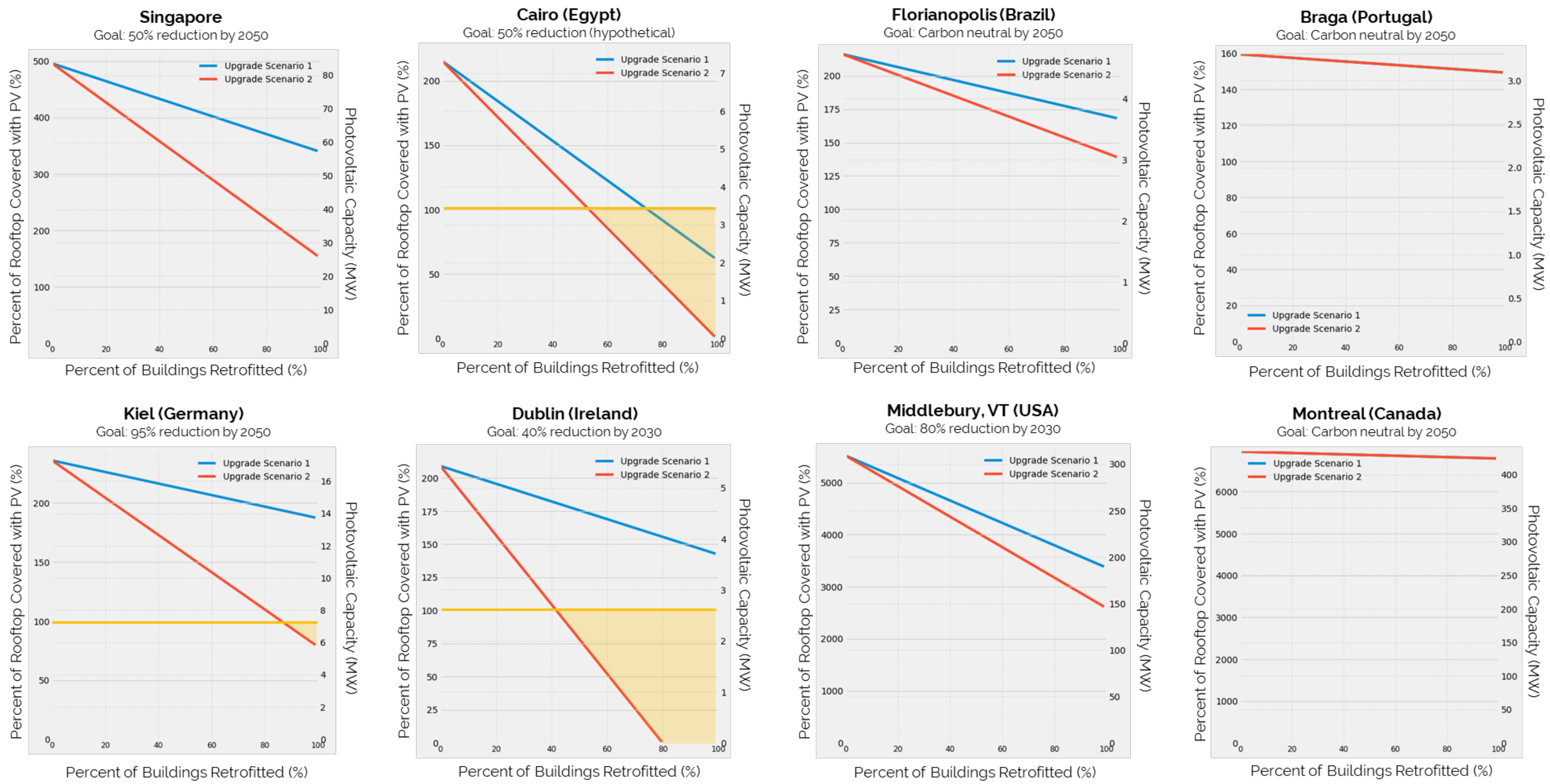


Figure 5-6: Emissions frontier curves illustrating the possible mix of technologies that the cities can adopt to achieve their longer-term carbon emissions goals.

5.3. Chapter Discussion

While many cities recognize the urgency to reduce carbon emissions of their building stock, the results suggest that municipal representatives, who are tasked to oversee the required changes, may underestimate both the enormity and urgency of the task at hand. For cities aspiring to reach (near) carbon neutrality such as Braga, Florianopolis, Kiel, and Montreal, even representative's definition of a deep retrofit of the entire building stock and 100% deployment of rooftop PV would not reach the goal. This means that those cities either need to adjust their goals or (more desirably) promote the use of more aggressive retrofitting measures such as Passivhaus level construction. Also, as previously reported (Gerdes, 2020) (Wang, Wang, & He, 2022) (Gaur, Fitwi, & Curtis, 2021), a key requirement for municipalities aspiring to reach a carbon neutral building stock is the decarbonization of heating through heat pumps which already offer demonstrated performance in all but the coldest cities investigated in this study. In Montreal, owners thinking of adopting heat pumps now face two barriers: It is currently cheaper to heat a building with natural gas and there is still widespread skepticism as to whether the latest generation of the air source heat pumps can reliably heat a building in such a cold climate. Of course, owners who decide today to switch to natural gas-based heating will likely remain with that technology for decades. Most participating municipalities also disregarded remaining fuel use from domestic hot water which faces the same dilemma as electrified space heating but currently seems to receive less attention.

It is worthwhile noting that the process to utilize UBEM.io to generate the seed UBEMs is more streamlined for cities that already have some form of GIS data comprising building footprints and heights (and / or are actively managing them). For example, the Singapore footprint GIS file was constructed by extracting data from OpenStreetMaps, with some manual measurements for heights, extrapolated from Google Maps / Earth. This required significantly more effort / time compared to e.g., Braga, which already possesses some form of GIS data more aligned with the requirements.

Technology adoption over time is a key, missing factor in this study. At a typical retrofitting rate of 1%, cities that can theoretically meet their 2030 targets through the tested technology pathways – such as Braga, Dublin, Florianopolis, and Singapore – would need to instantly boost their annual retrofit rate to 12.5%. As it stands, municipalities pursue building upgrades that are either insufficient or they work at implementation rates that are an order of magnitude too low.

Is there a productive way forward? Fortunately, there currently is significant political momentum to reduce carbon emissions in cities. The three-day workshop experiment reveals that municipal representatives tasked with implementing carbon reduction targets generally appreciate the use of data-driven methods to guide their policy development. Participating cities without previously established carbon reduction targets particularly benefited from the workshop as the UBEM simulations can help them to link targets to a particular set of measures. Florianopolis, for example, reported its intention to use the results from the workshop to establish dedicated carbon reduction goals for buildings.

Another workshop finding is that the specific set of technology measures investigated in each city significantly varies due to climate, political, and economic boundary conditions as well as the state of existing buildings. There is no one-size-fits-all approach for the built environment. It is therefore encouraged that municipalities around the world to conduct similar data-driven studies to establish baselines and predict the saving potential for a variety of technologies. Given that it took us three days and four instructors to get eight groups to conduct a carbon reduction study of a seed neighborhood, we conclude that our approach can be widely adopted.

Beyond the workshop, it is recommended that cities adopt a phased approach that ramps up activities in terms of depth and speed of retrofits to bring the built environment towards their final carbon emission reduction target. For equity reasons, the rate of retrofits should be consistent within jurisdictions and increase over time. Using UBEM results, policymakers can accordingly segment their jurisdiction and adopt more targeted incentive structures that consider building ownership, resident income, and other demographic factors. Implementing a phased approach allows policymakers to monitor key performance indicators and iteratively improve the implementation processes.

5.4. Chapter Summary

Politically driven carbon reduction goals for buildings are currently somewhat disconnected from technical realities in terms of both the extent of considered upgrades and the speed of implementation. It was demonstrated in the is chapter that recently developed urban building energy modeling workflows have matured to a point at which they can be widely applied and offer actionable information for municipal decisionmakers. Armed with these tools, municipalities can develop financial incentive measures that persuade sufficient owners to upgrade their buildings while training a workforce that can implement these measures.

Chapter 6

From Technology to Socio-Economic

Typical UBEM simulations and analysis consider only building physics and characteristics. However, energy use – especially in residential buildings – is also determined by socio-economic factors. This chapter presents a method using supervised and unsupervised data science / machine learning approaches to combine physical properties of buildings with socio-economic data from census, to understand the key parameters affecting energy use. It was found that socio-economic factors have a significant impact on building energy use patterns, and should be incorporated in archetype assignments in UBEMs.

6. From Technology to Socio-Economic

The previous chapter has shown that UBEMs can help policymakers and planners around the world make informed, data-driven decisions. However, urban building energy use is only not solely determined by building physics and characteristics. Socio-economic factors also play a significant role in energy use of buildings in regions around the world.

It has been widely reported that low-income households in the United States have disproportionately high energy burdens, since they spend a much higher share of their income on utility and energy bills – 8.1% of their income on energy costs on average, compared to 2.3% for non-low-income households, with utilities costing an average of $1.41 psf compared to $1.23 psf for non-low-income households[9]. High energy burdens are also known to correlate with other health, social, economic, and safety risks, such as greater probability of diseases, higher stress, economic hardship, and poverty. (Drehobl & Ayala, 2020).

Drehobl & Ayala (2020), in the American Council for an Energy-Efficient Economy (ACEEE) report, also highlighted that compared to white (non-Hispanic) households, Black households spend 43% more of their income on energy costs. In general, low-income household spend three times more of their income on energy costs than non-low-income households. Many cities also have more highly burdened residents, and national averages also do not tell the full story as there is significant regional variation in the energy burden that low-income households face (U.S. Department of Energy Office of Energy Efficiency & Renewable Energy, 2019).

The benefits of household energy efficiency improvement programs have been widely reported. For example, weatherizing and insulating homes can help reduce heating and cooling costs and improve indoor air quality. However, unique barriers exist in achieving energy savings in low-income households due to a myriad of challenges. While many households are eligible for the US Department of Energy's Weatherization Assistance Program (WAP) – which in theory provides a low-to-no cost home retrofit for homeowners – actual retrofits supported by WAP leads to only an average energy saving of 25%, far below the levels required to achieve emission goals. The disparity (and discriminatory) nature of energy burdens

[9] Low-income household as defined in the ACEEE Energy Burden report refers to households that are ≤ 200% below federal poverty level (FPL).

are exacerbated when considering that Blacks, Hispanics, and Native American own homes at lower rates than white owners (Edelberg et al. 2021).

Programs and policy levers serving low-income households must be thoughtfully designed and implemented. While current UBEM approaches can serve as effective tool for policymakers in the technology aspect, they are largely inadequate in addressing social-economic inequalities.

6.1. The Typical UBEM Archetype Approach (and Its Deficiencies)

The typical UBEM developed for stock-level carbon reduction strategies targeting neighborhood or city-scale adopts an archetype assignment approach. Archetypes, as described in Chapter 2, are composite representations of buildings with similar building properties and characteristics. Grouping the entire building stock in a city into archetypes, and assigning buildings simulation templates based on archetypes, make modeling thousands to hundreds of thousands of buildings much more manageable (as compared with manually assigning templates to individual buildings, one-by-one).

Researchers and / or building energy modelers typically assign archetypes based on experience, norms, or heuristics, with the most common being segmenting the building stock simply by program (residential, commercial, institutional, etc.) and age. This practice has been commonly adopted since the proliferation of UBEMs. Furthermore, energy modelers typically assume a single occupancy profile (behavior) across the entire archetype (or even archetypes) – for example, by assuming all households in an entire municipality utilizes energy in a comparable manner. This assumption ignores the fact that residents occupying the same housing type in the same city may rent or own, often have varying income, education, and cultural backgrounds. All these factors can have an impact on the energy use profiles of buildings that share the same physical archetype. These differences often extend form the individual household to whole municipalities.

For example, the cities of Evanston and Des Plaines, are both situated in Cook County, Illinois. They are approximately 13km apart. Form the outside, many residential units such as single-family homes look very similar in both cities (**Figure 6-1**). However, socio-economic demographics are significantly different. As reported by the census, Evanston has a per capital income of $53,532, 37% higher compared with Des Plaines ($33,342). Median household income in Evanston is relatively higher as well, at $82,470 compared with $67,636 in Des Plaines. The contrast in median value of owner-occupied housing units is equally stark, with Evanston's owner-occupied housing units being valued at 36% higher than those of Des Plaines ($395,000 in Evanston compared with $251,700 in Des Plaines).

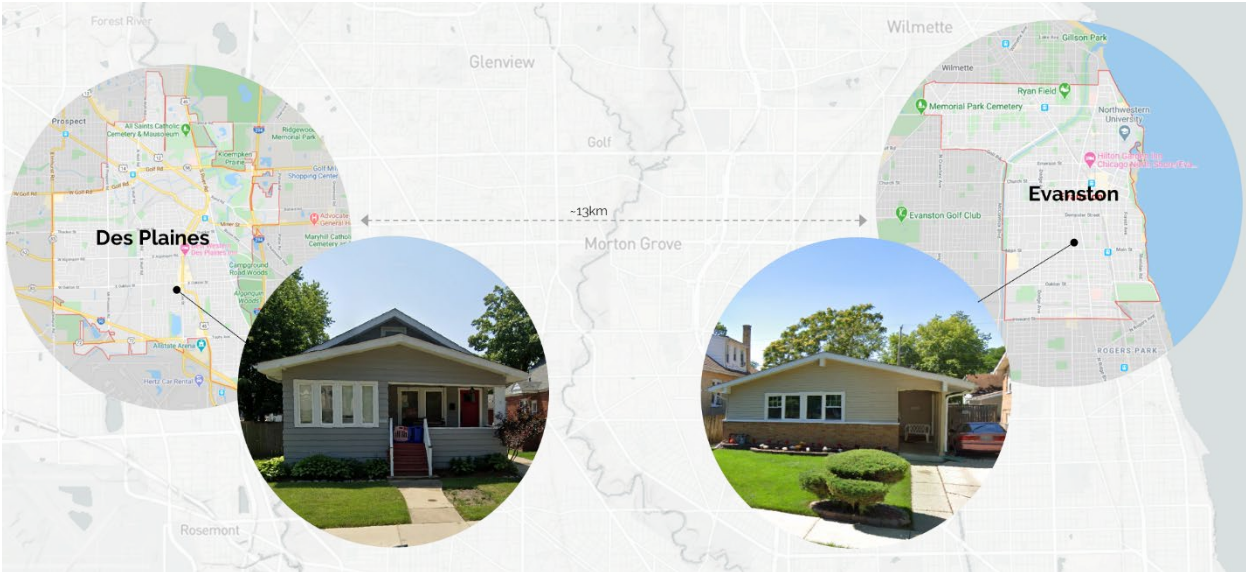


Figure 6-1: Single family homes in Evanston, IL and Des Plaines, IL.

With the energy models – which simply utilize simplified geometries for thermal simulations – expecting to be similar (and the building parameter templates expecting to be similar as well), conventional UBEMs cannot capture the socio-economic differences between the two cities.

Electric smart meter data is available in this research study for certain residential units in Evanston and Des Plaines, from a research collaboration with Exelon, a utilities company headquartered in the United States. Census data for these cities is also publicity available. These data are used to explore the impact and relationship between census (demographics) data and household electricity / energy use profiles.

The aim of this chapter is thus three-fold – *viz.* to cluster available data (i.e., smart meter readings) to better understand residential energy use patterns; to understand the effect of socio-economic parameters on UBEMs, and to make reasonable predictions / extrapolations for entire cities or municipalities based on only a subset of available data (which is typical given that smart meters are usually only installed in a subset of residential homes in cities. The city of Evanston, for example, has over 12,000 building footprints in the public open data repository, but less than 2% of these have metered electricity data. Similarly, the city of Des Plaines contains over 20,000 building footprints, but less than 2% smart meter readings were recorded in the dataset.

6.2. Methodology

The overall methodology, laid out in **Figure 6-2,** follows a three-stage approach:

Stage 1: Segmentation of over 400 electric smart meter time-series data into clusters representing typical user profiles in these cities.

Stage 2: Use the clusters found from Stage 1 to build a classifier, to identify which combination of building characteristics and census socio-economic data are important features to infer / predict what cluster a given household belongs to.

Stage 3: Use the classifier from Stage 2 to assign energy use profiles to each household in Evanston and Des Plaines, and run an UBEM for each city, to determine the impact of resident demographics of city level energy use.

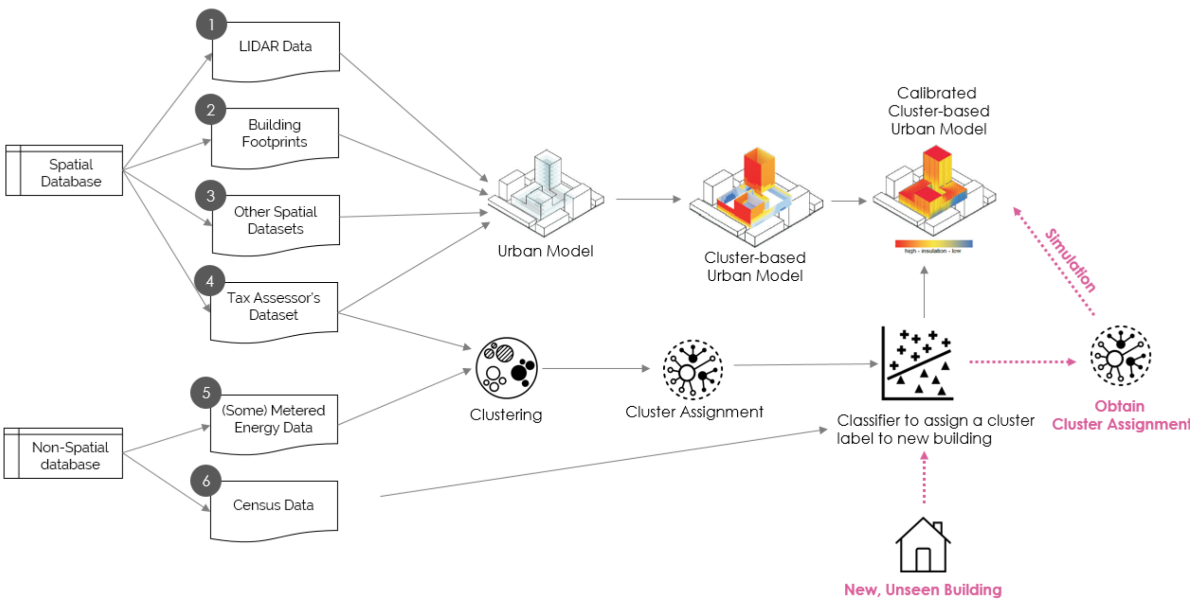


Figure 6-2: Overall methodology for chapter 6.

6.2.1. Stage 1 – Clustering

Data Preprocessing

The entire raw smart meter dataset was first pre-processed and installed onto a PostgreSQL database (**Figure 6-3**). The data was subsequently filtered. Specifically, data that are missing, incomplete and corrupted data were removed. This process resulted in 238 and 214 usable smart meter readings in

Evanston and Des Plaines respectively, recorded for the year 2017. The readings are further processed resulting in a data-frame comprising 96 columns of hourly data for the two consecutive coldest days in winter and two consecutive hottest days in summer – 6 (Friday) and 7 (Saturday) January 2017 and 21 (Friday) and 22 (Saturday) July 2017 respectively.

This approach has several merits. First, smart meter readings are usually incomplete with certain days or weeks not having recorded measurements. This (common) phenomenon was observed with this dataset. Second, by selecting one hottest / coldest weekday and one hottest / coldest weekend in both winter and summer, seasonal and diurnal trends are captured, ensuring that the discretionary usage patterns of the occupants are incorporated based on climate. Selecting a relative mild day may result in occupants not switching on their space conditioning systems, and the usage trends not being adequately captured. This approach is consistent with prior studies (Gianniou, Reinhart, Hsu, Heller, & Rode, 2018), but with considerations for keeping the dimensionality and parameters within reasonable ranges to derive meaningful and representative clusters.

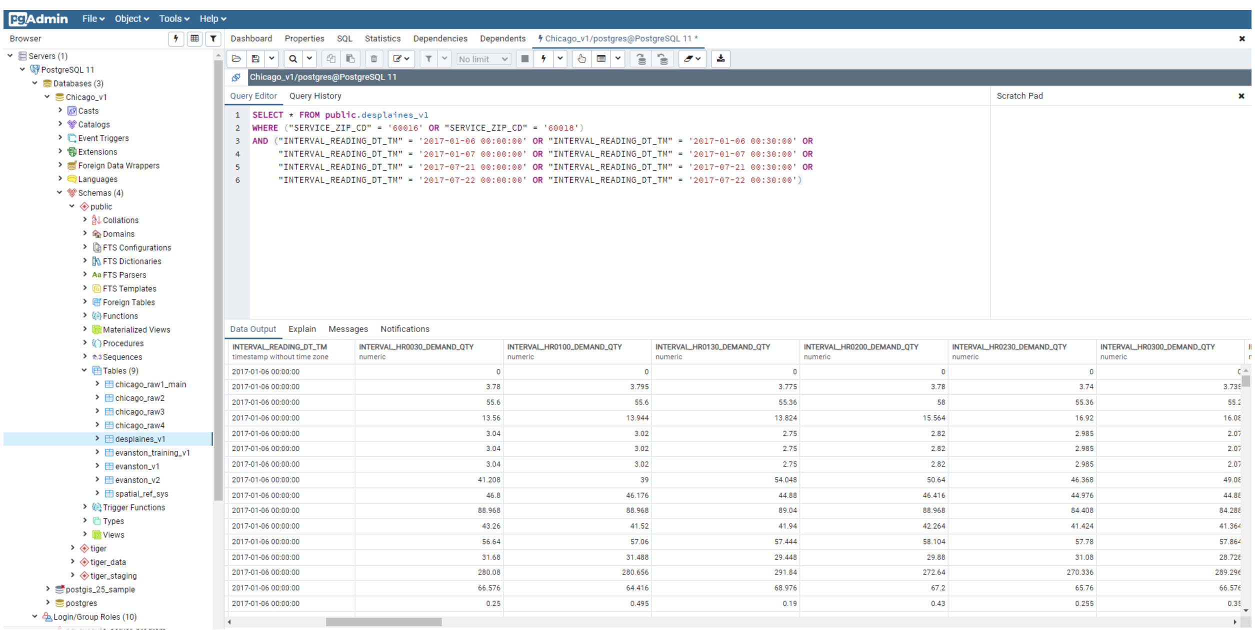


Figure 6-3: Screenshot of the PostgreSQL database implemented for the raw smart meter data.

Baseload de-minimization

The key interest of the clustering exercise is to characterize energy consumption profiles into similar clusters. Thus, an additional 'baseload de-minimization' step was undertaken prior to normalization.

Specifically, the daily minimum energy usage (in kW) was subtracted from each hour through 96 dimensions. This has two significant advantages. First, the daily minimum is a proxy for the building's 'baseload', present regardless of situation. This may include electricity consumption from equipment such as refrigerators, operational regardless of thermal conditions or occupant activities. Removing this 'baseload' allows isolation of the household's variable or discretionary usage, and helps distil true usage patterns. Second, this step helps prevent distortions during normalization, since normalizing profiles with relatively high baseloads may result in flattened or muted signals.

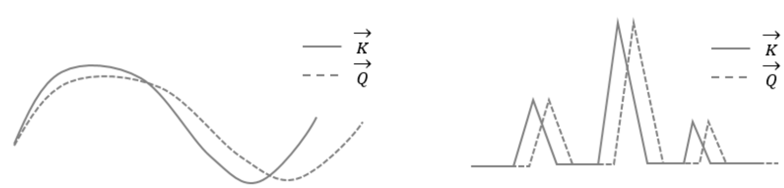
Dynamic time-warping and optimal cluster number

The typical clustering algorithms seeks to minimize within-cluster distance (cohesion) while maximizing between-cluster distances (separation). Unsupervised methods do not have target labels, posing validation challenges. Formally, the objective is to find:

$$\underset{\mathbf{S}}{\arg\min} \sum_{i=1}^{k} \sum_{\mathbf{x} \in S_i} \|\mathbf{x} - \boldsymbol{\mu}_i\|^2 = \underset{\mathbf{S}}{\arg\min} \sum_{i=1}^{k} |S_i| \operatorname{Var} S_i$$

where μ_i denotes the mean of points in S_i.

Typical clustering algorithms such as K-means utilize the Euclidean distance. However, similarity indices such as Euclidean or Manhattan, which aligns the *i*-th point on a time-series to the *i*-th point on another sequence, typically produce poor results for temporal (time-series type) data such as energy use. Consider the figure below with sequences of similar electricity use profiles but different lengths or slight time-lag. Distance metrics such as the Euclidean tend to produce undesirable results, as the similarities in shape and profile would not be captured.



The dynamic time warping distance metric supports similarity comparison between temporal sequences which may vary in speed. This non-linear and elastic alignment produces a more intuitive similarly measure, which allows for similar energy use profiles to match even if they are out of phase in the time axis. Using two cold winter days and two hottest summer days, the clustering feature set in this paper has 96 dimensions (i.e. $X \in \mathbb{R}^{96}$), each representing energy used (kW) for an hour.

Typical cluster selection methods include sihouette analysis, inertia / sum of square distances and the elbow method. The optimal number clusters for this study was selected based on a combination of these metrics to ensure proper clustering.

6.2.2. Stage 2 – Classification

The clusters allow better understanding of the load profiles in Evanston and Des Plaines. However, the number of units with smart meter readings only form approximately 1% of the total buildings in Evanston and Des Plaines. Thus, a method to predict / extrapolate the results to the entire cities is necessary. Another key factor is the necessity to understand how building properties and characteristics, as well as socio-economic variables, will affect how the clusters are assigned.

In this stage (**Figure 6-5**), the cluster labels derived are used as the dependent variables, and two sets of independent variables were obtained. The first, retrieved from cook county's public tax assessment data, contains information on the physical properties and characteristics of the buildings, including building age, number of rooms, and wall materials, etc. The second set contains socio-economic data retrieved from the census, containing information – at census block group (the finest level of granularity) – such as median household income, median age, and median household property value (**Table 6-1**).

Table 6-1: Variables included in the classification models.

Building Properties and Characteristics		Socio-Economic Data	
Variable	**Type**	**Variable**	**Type**
Building Age	Integer	Median Household Value	Integer
Number of Rooms	Integer	Median Income	Integer
Property Class (Type of Residential Unit)	Categorical	Median Age	Integer
Neighborhood Code	Categorical	Rental Percentage	Percentage
Attic Type	Categorical	Percentage Owned	Percentage
Basement Type	Categorical		
Wall Material	Categorical		
Roof Material	Categorical		
Central Air-conditioning	Categorical		
Central Heating	Categorical		
Other Heating Provisions	Categorical		

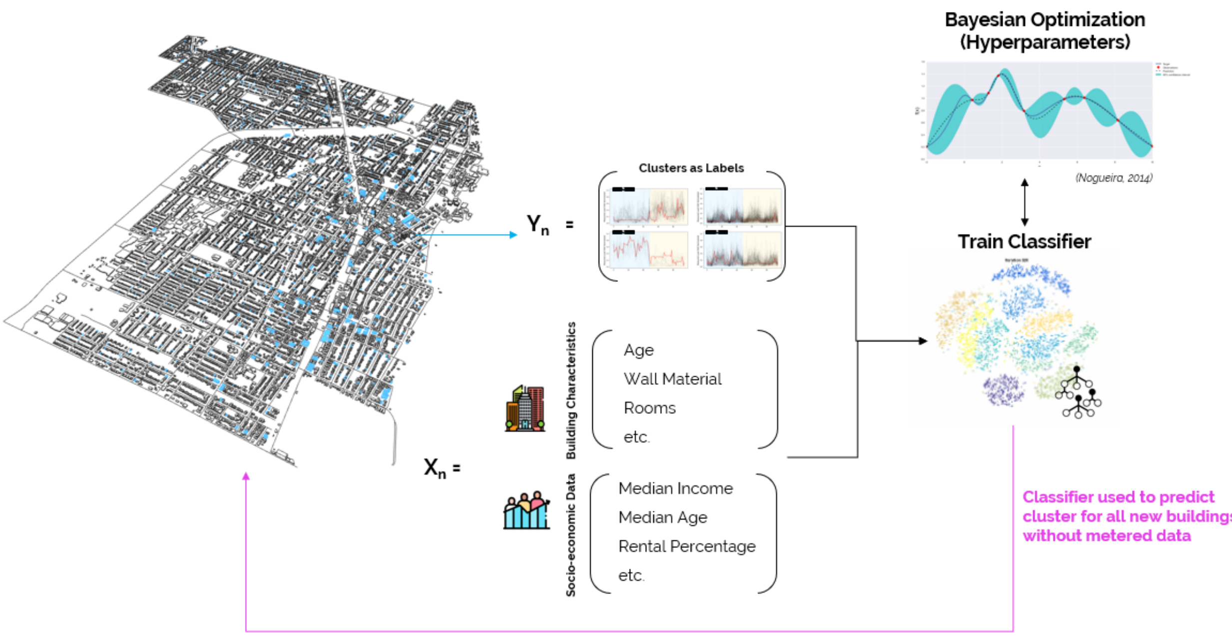


Figure 6-5: Process for stage two, where a classification model is developed using the cluster labels as the dependent variable.

Classification model

Different models were for the classification – Random Forest (Breiman, 2001), extra trees (Geurts, Ernst, & Wehenkel, 2006), and XGBoost (Chen & Guestrin, 2016). Neural networks were also initially considered but eventually dropped as it consistently performed poorly due to the method being unsuitable for sparse, categorical data which the dataset contain.

Random Forest is a tree-based, meta-estimator that fits a number of user-decided decision trees on various sub-samples of the dataset, and averages the predictions to improve results. The trees operate as an ensemble, and each tree produces a prediction which is then averaged. The large number of relatively uncorrelated trees operating in a committee / ensemble supposedly outperform any of the individual constituent model(s). The 'random' in Random Forest refers to the selection of a random subset of the data (bagging).

Like Random Forests, the Extra Trees classifier – also known as extremely randomized trees – introduces more variation into the ensemble by variating how the trees are built. Specifically, while Random Forest uses bootstrap replicas by subsamples the input data with replacement, Extra Trees simply uses the whole original sample. Another difference lies in the selection of cut-points when splitting nodes. Extra Trees selects the cut-points randomly while Random Forest chooses the optimal split. However, once the split points are selected, both algorithms simply select the best amongst all feature subsets. Extra Trees adds randomization but retains the optimization aspect.

XGBoost (eXtreme Gradient Boosting) is a gradient boosted decision tree-based ensemble model that, like Random Forest and Extra Trees, uses an ensemble to make predictions. However, while both Random Forest and Extra Trees use bagging to build full decision trees in parallel from random bootstrapped samples, XGBoost uses the boosting technique, which instead improves simple weak models by combining it with other weak models, to create a collectively much stronger model. Gradient boosting is simply an extension of the boosting technique, where additively generating weak trees / models is formalized as a gradient descent algorithm over an objective function.

The dataset is segmented into training (80%) and test (20%) sets out of 452 meter readings, where the model is trained iteratively on the training data and used to predict accuracy of the unseen test set. Bayesian optimization (Nogueira, 2014) was utilized to optimize the hyperparameters of the models, which includes the number of trees and tree depth, etc. The Bayesian optimization method constructs a posterior distribution of gaussian process (functions) that best described the function to be optimized, and as the number of observations increase, the posterior distribution improves and finally converges at a set of hyperparameters for each model. The samples for the training and test set were selected at random but kept consistent across the models for comparison.

6.2.3. Stage 3 – UBEM Simulation and Comparison

In the final stage, the best performing classification model (validated against an unseen test set) was used to predict the cluster energy use profile for all buildings that do not have smart meter readings. These cluster load profiles are included in the UBEMs as occupancy schedules based on the cluster assignment, and compared against conventional UBEMs.

6.3. Results

6.3.1. Stage 1 – Clustering Results

The clustering algorithm with dynamic time warping, after applying the baseload de-minimization, produced four unique cluster load shape profiles, presented in **Figure 6-4.** Further details for each cluster are shown in **Table 6-2**.

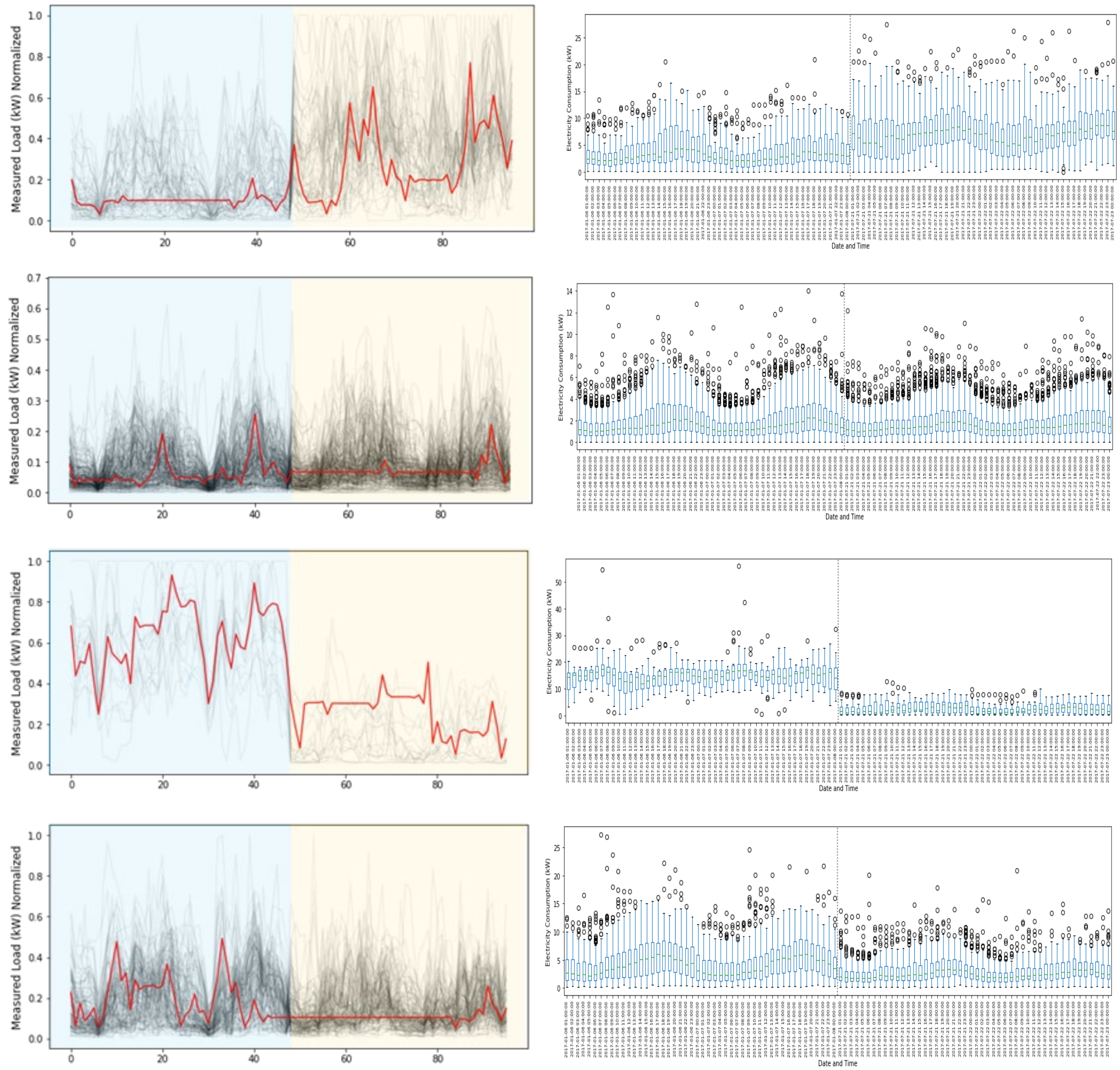


Figure 6-4: Four clusters found, with each row representing one cluster. The blue shaded area represents the profile for the two winter days while the orange shaded areas represent the profile for the summer days. The red lines depict the cluster centroids while the box plots show the range, variations, and hourly outliers within each cluster.

Table 6-2: Details of each cluster

	Cluster 1 *Exurban, Upper Middle Class*	Cluster 2 *County Typical*	Cluster 3 *Young, low income*	Cluster 4 *High energy users*
Units (Evanston)	28 (12%)	135 (57%)	6 (7%)	59 (25%)
Units (Des Plaines)	15 (9%)	82 (49%)	0 (0%)	72 (43%)
Median Age	42.4	41.9	34.9	41.8
Median Income	$87,473	$75,094	$63,042	$75,653
Percentage of Rental	40%	39%	51%	35%

Cluster 1 (Exurban, upper middle class): Cluster 1 contains 28 units in Evanston and 15 units from Des Plaines. This cluster exhibits an early afternoon peak for both winter and summer, although normalized energy use in summer is observed to be relatively higher than winter, and, in most hours, the highest among all clusters. Buildings in this cluster typically have relatively more rooms and larger overall area (4+ rooms on average). The occupants also possess the highest median income and age, signifying the possibility of relatively well-off older adults or retirees in the cluster demographics.

Cluster 2 (county typical): Cluster 2 contains 135 units in Evanston and 82 units in Des Plaines. This cluster can be described as the county typical profile. Most residential units in this clustering study belong to this cluster. The load profiles are relatively typical and predictable – lower in the morning, ramping up over the afternoon to evenings as the day progresses. This is likely the middle-class families / households with relatively average energy use patterns. Cluster 2 also has a high percentage of homeowners (61%).

Cluster 3 (young, low income): Cluster 3 contains no units in Des Plaines and 7 units in Evanston. It is the smallest cluster in this study. The median age is lower than all other clusters at 34.9, and the median income is the lowest as well ($63,042). The percentage of rental, on the other hand, is the highest at 51%. The units in the cluster are also the newest. This cluster has the most unpredictable load profile with relatively high energy use in winter, suggesting that possible usage of electric space heaters. It is possible that most occupants in this cluster are students (possibly from Northwestern University in Evanston).

Cluster 4 (high energy users): Cluster 4 contains 72 units in Des Plaines and 59 units in Evanston. Median age is relatively similar to cluster 1 and cluster 2, but rental percentage is the lowest at 35%. The load profile follows a similar trend as cluster 2 but with higher diurnal variation and peaks (wider energy use range). Electric space heaters are also likely. This suggests that some of the units here may belong to older units that are less energy efficient.

6.3.2. Stage 2 – Classification Results

The results of the tree-based models are shown in **Table 6-3**. The Random Forest model was selected based on having the highest accuracy across the three models on the test set. It is worthwhile to note that a random allocation / guess will yield around 25% accuracy, and so the models are deemed to have performed significantly better. More importantly, in this study, the cluster assignments are hard clusters where cluster membership is binary in nature (either belonging to a cluster or not – belonging to only one cluster with the averaged prediction from the ensemble models), but it is also viable to do soft / fuzzy clustering where each unit can belong to more than one cluster, with a fuzzy coefficient or probability applied to each cluster assignment. The choice of using hard clusters for this study is deliberate since one user profile will be used for each residential unit in the UBEM. In this context, soft / fuzzy clusters are beyond the scope of this study. Using tree-based models also provide for a consistent basis for comparison across interpretable machine learning methods. While both neural nets and tree-based models can model non-linear relationships, neural nets are typically more ‘black-box’ and less explainable / interpretable.

Table 6-3: Comparison of classification models

Classifier	Accuracy (Training Set)	Accuracy (Test Set)
Random Forest	**0.75**	**0.55**
Extra Trees	0.92	0.52
XGBoost	0.62	0.52

In **Figure 6-6**, it can be observed that a single decision tree contains multiple nodes and branches, where every node is a condition of how to split values in a single feature, so that similar values of the dependent variable will end up in the same set after the split. The condition for classification models is typically based on impurity – i.e., Gini impurity / information gain (entropy). Feature importance (or variable importance), in this context, describes which features are more important / critical and relevant in the tree-based model that decides the split and resultant classification. Feature importance in tree-based models can support analysis in various ways such as providing better understanding of the model’s logic, helping to identify key variables, and supporting variable selection. In the context of this study, feature importance in the tree-based models can help identify which are key variables – between the variables in the building characteristics / tax assessor data set and the socio-economic / census set – affecting the model’s prediction of the user energy use profile.

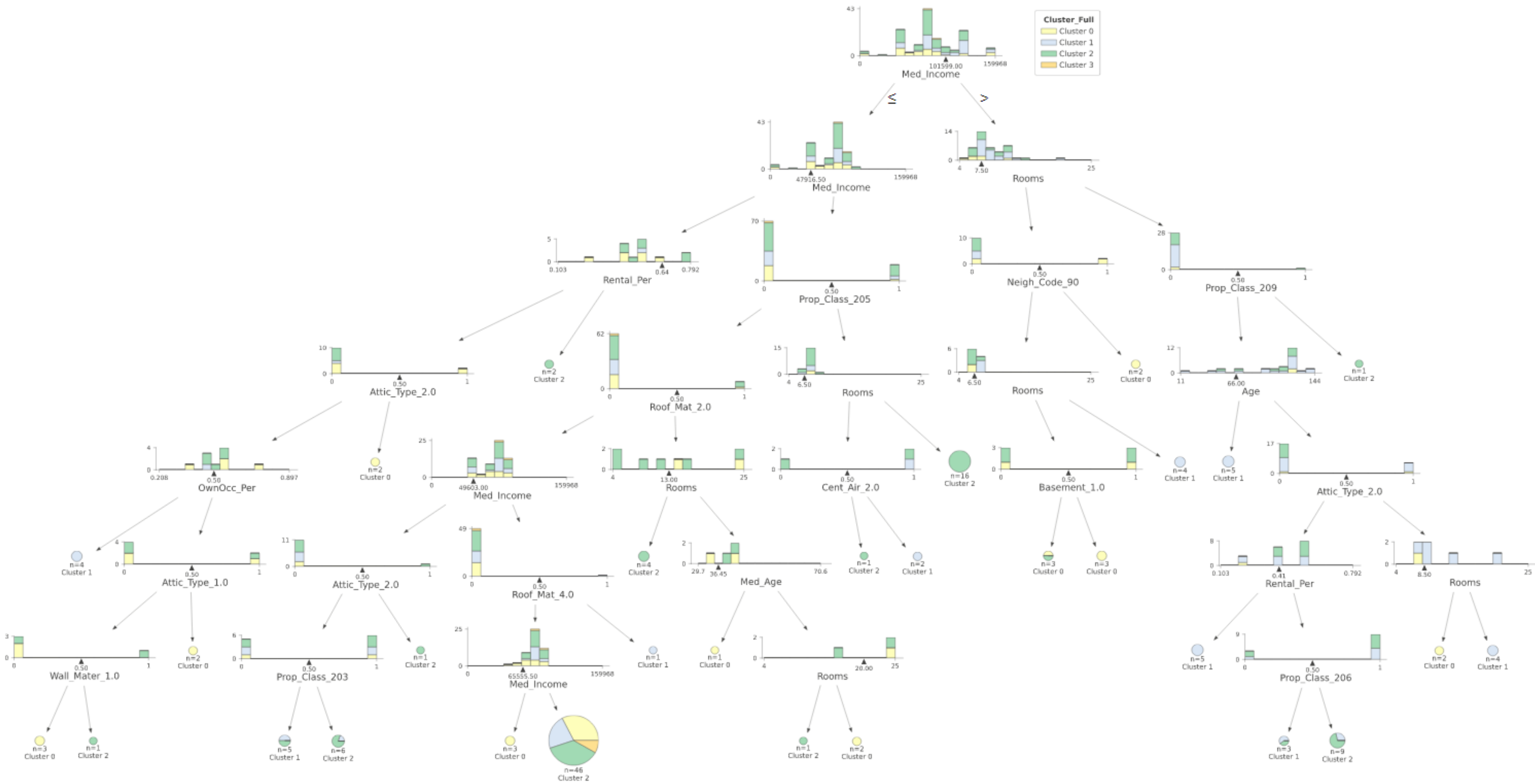


Figure 6-6: Sample decision tree from the Random Forest model

Figure 6-7 shows the feature importance for the best performing model (Random Forest), with the x-axis representing the normalized feature importance on a scale of 0 to 1. It was observed that *building age* and *number of rooms* (proxy for program in residential buildings) are the most important features in the best Random Forest model, followed by the socio-economic variables including *median household value*, *median income*, *percentage of rental units* and *median age.*

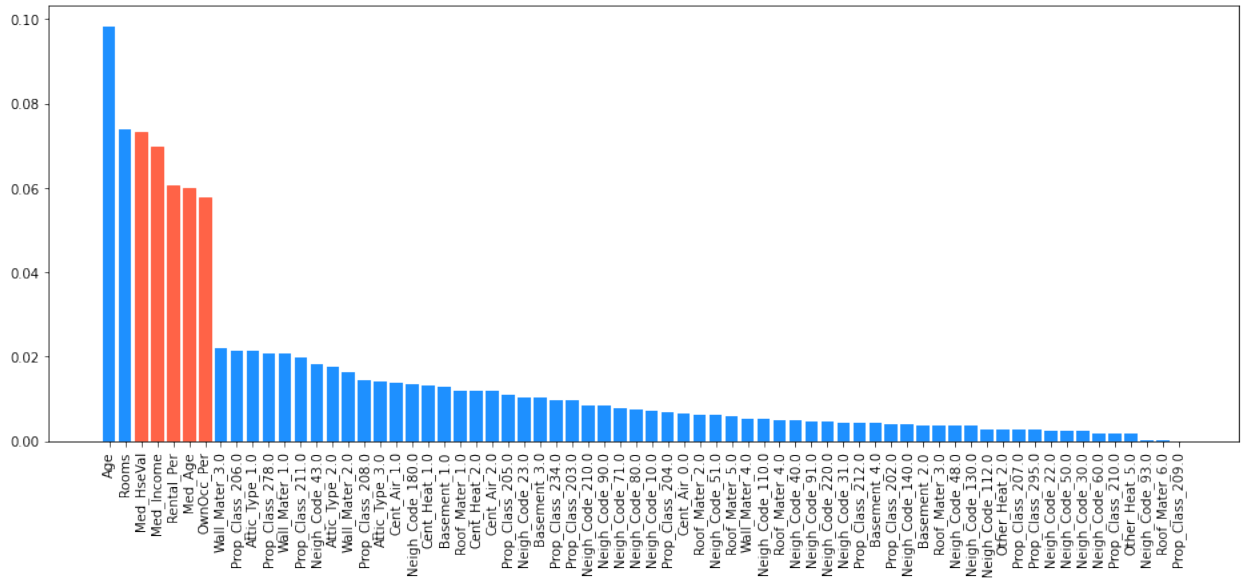


Figure 6-7: Feature importance for the best performing Random Forest model.

Figure 6-8 shows the partial dependence plots for the variables *age* and *median income*. Partial dependence plots serve the purpose of illustrating the marginal effect a specific feature has on the predicted outcome of the machine learning model (Friedman, 2001). The figure shows that the partial dependency of *age* decreases as the age of the units increased above 50 years old. On the other hand, the partial dependency of the *median income* variable increased at $50,000 and subsequently increased again at $100,000. This signifies that in the Evanston and Des Plaines building stock, buildings at 50 years of age and income levels at $50,000 and $100,000 are important inflexion points affecting building energy use profiles and patterns.

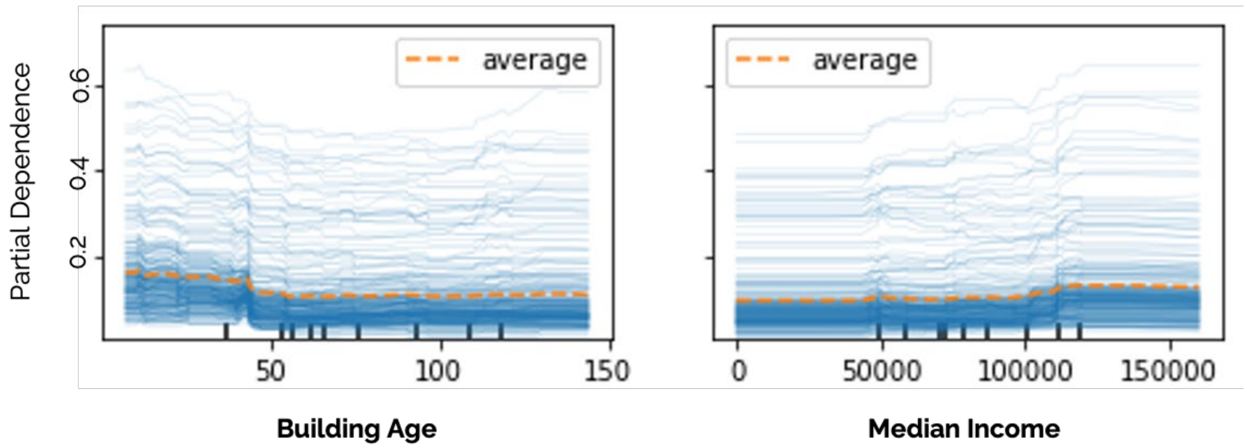


Figure 6-8: Partial dependencies for building age and median household income

6.3.3. Stage 3 – UBEM Simulation Results

In the final stage, the Random Forest Classifier developed in Stage 2 was used to predict a cluster load profile for every single building footprint in Evanston and Des Plaines. **Figure 6-10** shows the EUI distributions for both UBEMs for the two cities, using the conventional method of assigning just one user / occupancy profile vs one of four clustered profiles from the classifier prediction. It was observed that in Evanston, the entire EUI distribution shifts by approximately 10% to the right, while the EUI distribution for Des Plaines shifts by just ~2.5%. This is an interesting observation given that Evanston has a higher median income and median household value. **Figure 6-11** further illustrates that the conventional UBEM simulations consistent underestimates the energy use across the entire year, compared with the cluster method.

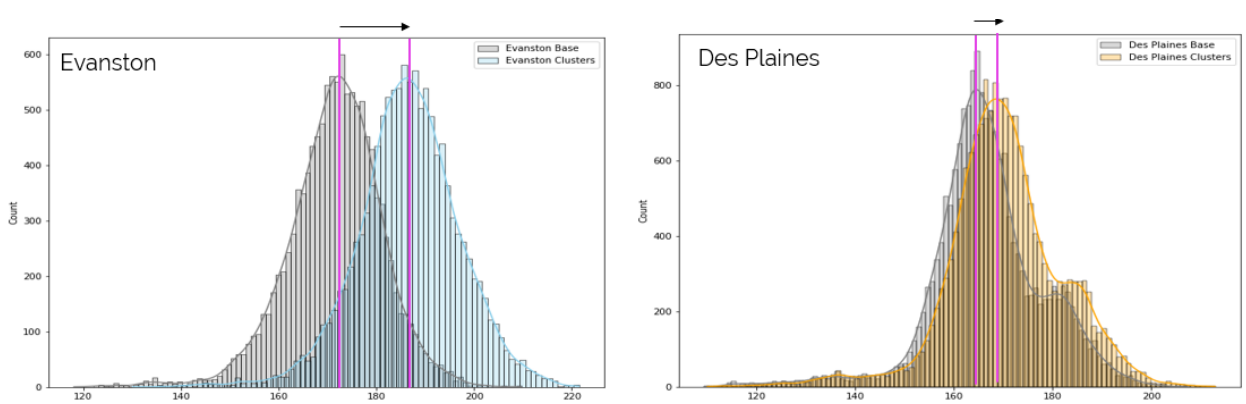


Figure 6-10: EUI distribution for Evanston and Des Plaines for the UBEMs using the conventional method of just assigning a single occupancy profiles vs the method of assigning a cluster based on the classification model.

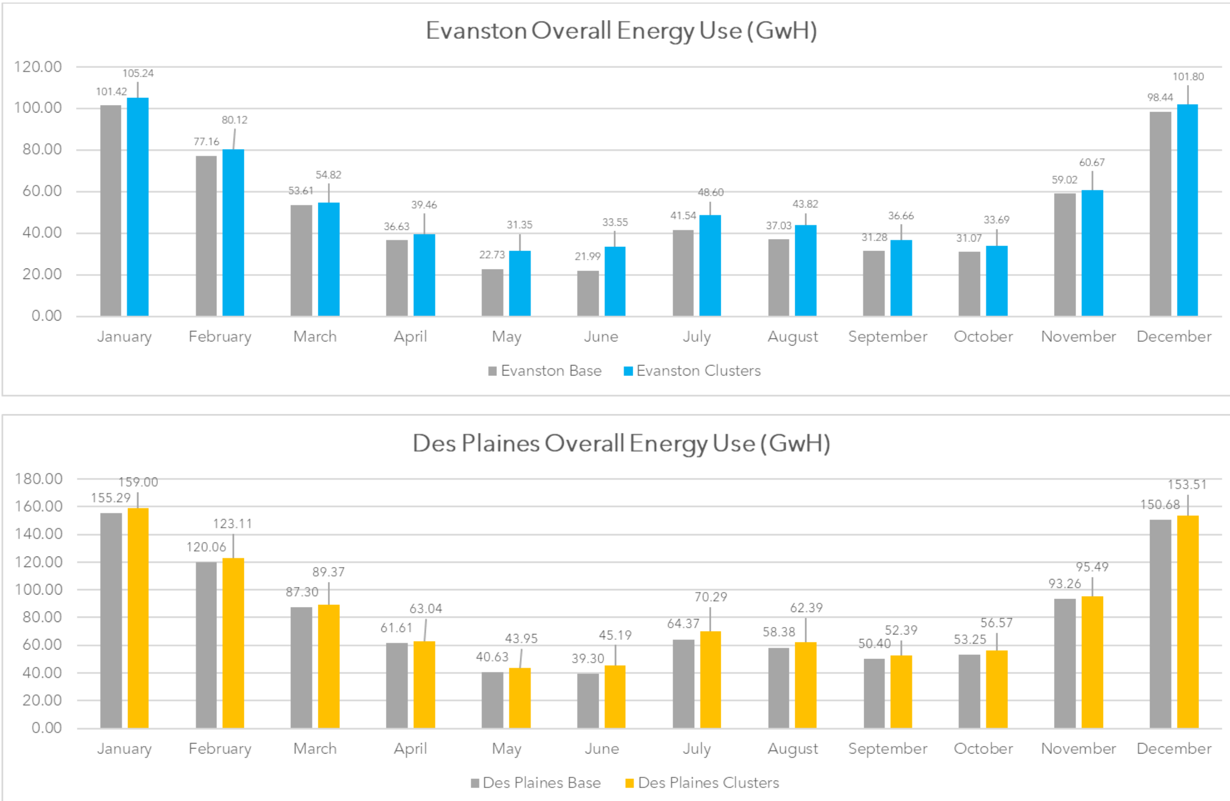


Figure 6-11: Month energy use comparison between the conventional UBEM method vs the cluster assignment method, for Evanston and Des Plaines.

6.4. Chapter Discussion

The findings in this chapter have demonstrated that it is feasible to combine conventional UBEM simulations based on building properties / characteristics with socio-economic data. The findings also suggest that these socio-economic factors, such as median income and median housing value, can influence building energy use by ~10% across the entire city. This means that it is worthwhile understanding these relationships better, and important to integrate physics-based models with socio-economic parameters, so that policy design and interventions are more realistically aligned to reality. This chapter marks the beginning of such a field of inquiry. Looking ahead, the socioeconomic realities of occupants have wider-reaching repercussions including residents' ability and willingness to retrofit their buildings.

In this study, the data were anonymized and aggregated such to prevent individual buildings / properties from being identified. However, this is a possibility, and future studies should take note of privacy and ethical concerns when manipulating similar data.

6.5. Chapter Summary

In this chapter, it was demonstrated that although building characteristics and physical properties such as building age and size of residential units are key factors affecting building energy use, social-economic variables are equally important – and in this case of Evanston and Des Plaines found to be more important than many other building physics variables. Conventional UBEMs generally do not take these into account, while on the other hand, policymakers and economists do not utilize physics-based models to make data-driven decisions.

Typical UBEMs generally only considers building properties and characteristics, but socio-economic factors are important determinants of energy use as well. This chapter presents a data-driven method combining supervised and unsupervised data science / machine learning to provide better inference of residential load profiles / patterns, and to extrapolate (predict) the results across entire cities. Data from two nearby cities were utilized. It was found that apart from age and program type, socio-economic factors such as median household income and median occupant age are key parameters affecting energy use profiles.

Additionally, this chapter has shown that demographics and socio-economic parameters matter and influence energy use. If no interventions are being made through thoughtful incentive programs, these differences will further a trend where the difference between the groups will become even more pronounced, as building retrofits will be concentrated at higher income level households who can afford it – further exacerbating the energy burden and in a broader sense, inequality – potentially leading to impediments and reduced carbon emissions reduction.

Chapter 7

Conclusion

This chapter revisits the hypotheses from Chapter 1, and discusses potential future research directions.

7. Conclusion

7.1. Feasibility of Contributions

Chapter 3 provides the framework delineating four key use cases for UBEMs, and proposed a minimum viable model for each use case. The minimum viable models ensure least effort is required to develop workable UBEMs that can be quickly deployed.

To overcome the resources and high effort levels required, and to provide a linkage between the key stakeholders required for implement UBEMs in policy design and development (*viz.* sustainability champion, urban planner, and energy modeler), Chapter 4 introduces UBEM.io, a web-based framework for rapid generation of UBEMs. UBEM.io has been first piloted test using datasets from the city of Evanston. In the pilot, it was found that using UBEM.io leads to a 46% reduction in man-hours required to develop a seed UBEM for municipal level assessment and analysis.

Further in Chapter 5, through the collaboration with eight cities around the world, the policymakers were able to develop seed UBEMs for their desired regions, and study the implications of shallow and deep technologies and retrofits to meet their targeted carbon emissions goals. The study framework presented allows for a methodological process for policymakers to identify potential technology pathways towards energy efficiency and carbon emissions reduction goals.

The findings in the workshop, and the research work with representatives from the eight cities demonstrated that UBEM can be an effective tool to help policymakers make data-driven decisions, and to identify and analyse potential pathways to impact.

In the study presented in Chapter 6, a three-stage method was proposed to first cluster available smart meter data in two cities, and use the results as dependent target variables in a tree-based classification model. Two sets of data were further served as independent variables. These include building properties and characteristics from tax assessments in Cook County, as well as socio-economic parameters from the US census. Finally, UBEMs were constructed to compare between the proposed method and the conventional method of simply assigning one occupancy profile for residential units.

The results and findings – especially the variable / feature importance retrieved from the best performing tree-based model (Random Forest), show that apart from building age, size of units and program, socio-economic parameters such as median housing value, median income, occupancy status (rented or owned) and median occupant age are important variables affecting energy use profiles and patterns.

7.2. Relevance

This dissertation has provided use cases and examples of studies conducted with cities around the world, where policymakers and city representatives utilized the results and analysis provided by the seed UBEMs to identify technology pathways towards carbon reduction. The city representatives have also expressed desires to develop more equitable policy interventions targeting underprivileged or underserved regions. In Chapter 6, it was also found in the tree-based models that socio-economic factors consistently rank high in the feature importance.

Therefore, the utilization of UBEMs in policymaking processes is relevant, and can provide relevant insights and easily digestible / understandable milestones towards their city's / municipality's carbon reduction goals.

7.3. Justifiable Effort

The minimum viable UBEM framework for the four use cases demonstrated that in combination with UBEM.io, UBEM generation with building parameter template assignment can be largely automated to a significant extent. Key stakeholders in cities and municipalities and the work they need to complete can also be streamlined using processes and tools such as UBEM.io.

The required effort, resources, data requirements, man-hour and cost to develop UBEMs – considering the time during the pre-workshop meetings and the workshops as described in Chapter 5 – amounted to less than one week. Thus, the required effort to develop seed and minimum viable UBEMs are far lower than the potential value capture and can therefore be justified.

7.4. Urban Modeling Across Multiple Dimensions and Scales

This section lays out a vision of how the concepts, methods and frameworks developed for this dissertation can be used across various scales, incorporating various aspects of urban planning and policy development. This section is exploratory rather than conclusive. Urban planning and policymaking are domains that are multi-faceted, multi-disciplinary in nature, involving a myriad of disciplines and stakeholders. Every policy lever also has specific goals, but at a macro / city-level, the priorities can be constantly changing. For example, while building energy use is a critical factor in achieving carbon emissions reduction targets, cities may choose to focus on different technologies or even entirely different means towards the objectives (such as industry / manufacturing or transport). However, it is common for the various disciplines involved to work in silos, often neglecting the key (political, socio-economic, and cultural) nuances and inputs required from other domains. It is common for every discipline to perceive its work as being the most critical, and thereby being blindsided by other important factors. In this context, it is important to consider urban modeling across multiple dimensions and scales.

7.5. Outlook

Although this dissertation presented several novel advances, further work is necessary to democratize and foster wide utilization of UBEMs (and urban-scale modeling in general).

Rapid, automatic calibrated living UBEMs

Cities are evolving and ever-changing ecosystems. While the use cases and methods presented allows cities and municipalities to rapidly prototype and generate UBEMs for policymaking, a city's priorities, composition, and key contributing variables are constantly evolving. Future work could focus on living UBEMs that are automatically updated and calibrated based on the city's evolving needs and data.

Multi-dimensional urban modeling

This dissertation primarily focused on UBEM, and its various methodologies, tools, and frameworks. While the approach is effective and feasible for policymakers and city representatives focusing on energy, urban scale building energy use is intertwined with many other aspects, such as transportation. For example, the proliferation of electric vehicles and the charging infrastructure required is poised to immense implications for energy / electricity use in buildings. Future research could therefore expand the linkages of urban scale energy use with areas such as transport, daylighting, industry, etc.

Enhancing energy equity

Energy burden and poverty are real and challenging issues that underprivileged, low-income and / or underserved communities around the world face – as described in Chapter 6. While the methods laid out in the chapter provide a framework for better inference and predictions, much can be done to testbed and implement the concepts to urban-scale policy design and development. It is important that these methods are iteratively refined, improved, pilot-tested and validated in realistic experimental or practical settings for positive outcomes.

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