# Building Archetype Calibration for Effective Urban Building Energy Modeling

by


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Submitted to the Department of Architecture
In Partial Fulfillment of the Requirements for the Degree of

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## Abstract

In response to the current environmental challenges, city governments worldwide are developing action plans to both reduce GHG emissions and increase the resilience of their built environment. Given the relevance of energy use in buildings, such plans introduce a variety of efficiency and supply planning strategies ranging from the scale of buildings, to full districts. Their implementation requires information about current building energy demands, and how these demands, and the city's energy ecosystem at large, may change as a result of a specific urban intervention. Unfortunately, metered data is not available at a sufficient level of detail, and cities face an "information gap" between the aggregate scale of their emission targets, and the scale of implementation of energy strategies. To close it, municipalities and other interested stakeholders require modeling tools that provide accurate spatially and temporally defined energy demands by building. Urban Building Energy Models (UBEMs) have been proposed in research as a bottom-up, physics based, urban modeling technique, to estimate energy demands by building for current conditions and future scenarios. Given the large number of data inputs required in their generation, UBEMs have relied on their characterization through "building archetypes". Yet, in the absence of detailed building and energy data, this process has remained somewhat arbitrary, relying on deterministic assumptions and the subjective judgement of the modeler. The resulting simplification can potentially lead to predictions that misrepresent urban demands and misinform decision makers.

In order to address these limitations and enable the large scale application of UBEMs, this dissertation introduces a set of modeling and calibration techniques. First, in order to demonstrate the feasibility of citywide municipal UBEMs, an 80,000 buildings model is generated and simulated for the city of Boston, based exclusively on currently available and maintained municipal datasets. An automated modeling workflow and a new library file format for archetypes are developed for that purpose, and current limitations of municipal datasets and practices are identified. To improve the reliability of UBEMs in reproducing metered demands, a new calibration approach is proposed, which applies principles of Bayesian statistics to reduce the uncertainty in archetype parameters defined stochastically based on a sample of metered buildings. The method is demonstrated and validated in the model of a residential district in Kuwait with 323 annually metered buildings, showing errors below 5% in the mean and 15% in the variance when compared with the measured EUI distribution. The accuracy of the resulting UBEM when reproducing EUI distributions is also compared with typical deterministic approaches, resulting in an error improvement of 30-40%. The method is expanded for its application when monthly energy data is available, and applied for the calibration of a sample including 2,662 residential buildings in Cambridge, MA. Finally, the relevance of calibrated archetype-based UBEMs in urban decisions is discussed from the perspectives of policy makers, energy providers, urban designers and real estate owners in two application cases in neighborhoods of Kuwait City and Boston.

Thesis Supervisor: Christoph F. Reinhart
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# Table of Contents

Chapter 1

# Introduction

Cities are both the most vibrant productive human creations and one of the main sources of global environmental impacts, a reality which is only going to become more acute as time progresses. The United Nations estimates that the number of city-dwellers worldwide will grow until 2050 at a net rate of about five million per month, largely via informal settlements and haphazard densification [1]. As a result, urban-related greenhouse gas (GHG) emissions are at an all-time high, with energy consumption in buildings being a key contributor, accounting for 22% of emissions in the United States and for almost a third globally [2]. Unless current emission rates are dramatically reduced, city populations will experience unmanageable climate change consequences, including increases in temperature and extreme weather events [3]. An example of such episodes was storm Sandy, which hit the North East of the United States in 2012, leaving without power large sections of downtown Manhattan (Figure 1-1). These changes will heighten the stress on the existing urban energy infrastructure, resulting in energy access limitations and more frequent power outages [4], especially harmful for informal or underserved communities.

In response to these global environmental challenges, city governments worldwide are developing action plans that set ambitious long term emission reduction targets such as 30%, 40% and 60% reductions by 2025 (New York, San Francisco and London) or 80% by 2050 [5–7]. Given the relevance of energy use in buildings, municipalities are introducing a variety of *energy efficiency* and *supply planning* strategies ranging from the scale of buildings, to that of neighborhoods and districts. The former involves policies for retrofitting existing building envelopes or equipment, and for ensuring that new construction follows modern performance standards. The latter measures comprise a variety of initiatives, being tackled by both cities and energy providers, including distributed generation, power storage, and district systems, which require the effective management and optimization of energy demands.

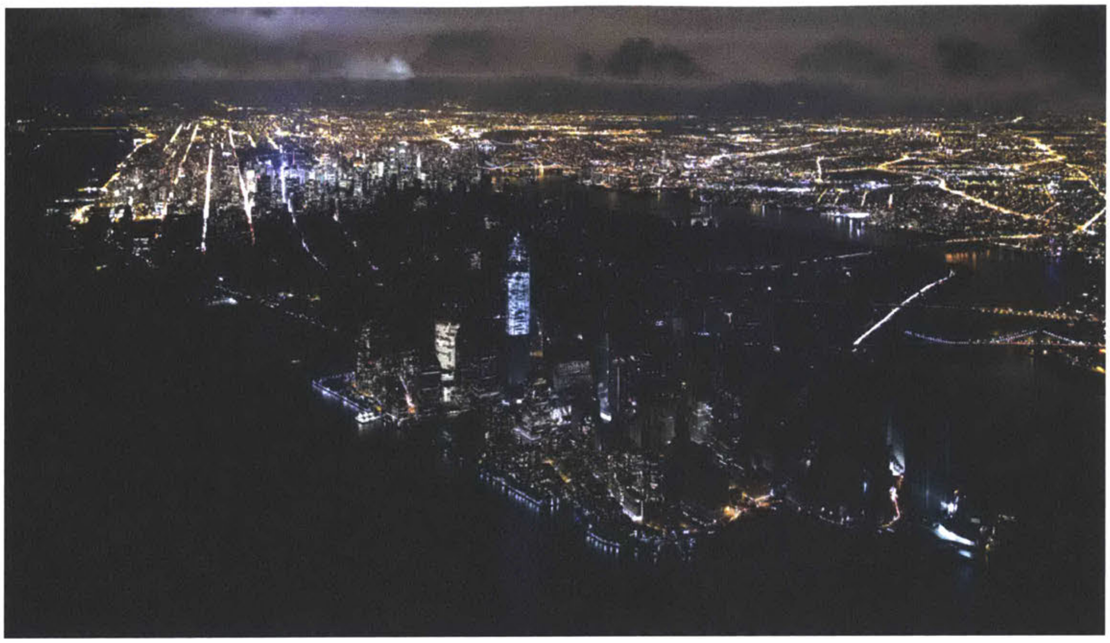

*Figure 1-2: NYC after Sandy storm (Iwan Baan 2012)*

While these strategies point in the general direction of a better energy future, both in terms of GHG emission mitigation and resiliency of urban energy systems, their practical implementation requires a dialogue between municipalities and other relevant stakeholders (building designers, real estate owners, utility companies, energy generators, etc.) over specific urban interventions. All parties involved in an energy related decision need to know which specific buildings and neighborhoods will be affected, what their current energy consumption is, and how that demand will change in the future should that decision be made. That conversation is not possible in the absence of current building energy demand data, and the understanding of how this demand, and the city's energy ecosystem at large, may change as a result of a potential intervention. Regarding existing buildings, energy consumption is routinely measured by utilities for billing purposes at annual or monthly timescales, and the increasing use of "smart metering" in buildings (45% electricity customers in the US) [8] is making demand data available at lower temporal scales. However, this information is rarely available for urban decision makers due to privacy and legal concerns, and their access is limited to anonymized and aggregated datasets, which are not sufficient for informing building-related urban strategies. While recent mandatory programs for energy disclosure in large cities like Boston or New York [9,10] are addressing these limitations, they typically only target large commercial or city owned buildings. The difficulty is even larger in the case of energy planning for new urban developments or future conditions, since building demands need to be modelled based on limited available information. As a result of the lack of access to detailed building energy data, cities face an "information gap" between the aggregate scale of their emission reduction targets, and the scale at which urban strategies need to be evaluated and implemented (Figure 1-2).

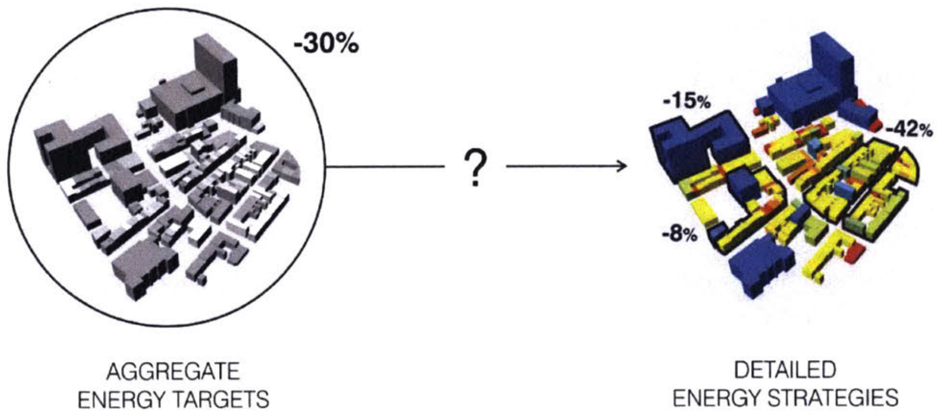


*Figure 1-2 – The energy information gap*

In addition to climate related policies, this gap also limits the capability of local governments to deal with issues of fuel poverty, weather vulnerability, and power grid resiliency which need to be addressed simultaneously. To close it, municipalities and other interested stakeholders require modeling tools that provide realistic spatially and temporally defined energy demands by building. Furthermore, such tools need to be based on currently available and actively maintained urban databases so they can be effectively implemented in practice.

## 1.1 The problem of modeling urban building energy use

Over the last decades, the problem of predicting or estimating the energy demands of buildings has been addressed at two very different scales: The building stock analysis level, of interest for policy makers, and the individual building design level relevant in architecture and engineering. To understand building energy demand patterns within cities, different types of modelling techniques inherited from stock analysis methods have been proposed over time, falling in two main categories: "top-down" or "bottom-up" models [11]. "Top-down" models link aggregate energy use to statistical variables, such as population trends and economic activities [12], but are not well suited for the analysis of small spatial and temporal units. "Bottom up" models on the other hand, apply statistical or "engineering" analytical methods to represent each building individually [13] and offer a more appropriate scale of analysis for urban decision making. However, by definition they require large datasets of metered building demand data, and do not offer enough flexibility to model detailed urban development or future technology scenarios. To address the shortcomings of existing large scale techniques, Urban Building Energy Modeling (UBEMs) is a new simulation technique that has been [14] proposed as a hybrid approach that combines bottom-up stock modeling with physics based simulation methods. Within an UBEM each building is represented as a thermal model, based on the same heat transfer principles that govern individual building energy models (BEM) [15].

BEMs are part of the established field of computer-based building performance simulation (BPS), and are applied in architecture for design development, code-compliance and improved operation of individual buildings. They can be generated and simulated through available tools such as EnergyPlus, ESP-r or TRNSYS [16–18], and provide outputs ranging from heating and cooling needs to indoor thermal conditions based on a variety of information about the building ranging from construction and usage patterns to surrounding climate. Being based on the same modeling approach, a calibrated UBEM can – in principal – be used by urban planners and policy-makers to evaluate current and future energy demands, with high spatial and temporal detail, as long as sufficient information about the buildings and their operation is provided. UBEM results can then be combined with mapping techniques to support energy certification and fuel poverty policies [19,20], or with power grid distribution models to evaluate the dynamic performance of urban energy systems [21]. As with BEMs, the generation of an UBEM requires the definition of numerous data inputs for both the building geometry and a large set of non-geometric energy related parameters (constructions, systems, usage patterns, loads, etc.). However, the established processes of model setup for individual buildings cannot be applied directly at the urban scale due to larger model sizes and lower data availability, requiring the use of various abstraction and simplification techniques. Multiple methods have been introduced for both the generation of building geometry from GIS or LIDAR datasets as well as their transformation into simplified thermal models with reasonable simulation times [22].

The remaining parameters however (such as number of occupants or level of insulation) represent a much larger modelling challenge, since municipalities typically store very limited data about their building stock, and building usage and operation details are necessarily unknown at this scale. Borrowing from bottom-up stock modeling practices, UBEM research has so far relied on the characterization of these parameters through "archetypes". An archetype is an average representation of a group of buildings with similar use, vintage, etc., used to define the whole group [23,24]. Yet, in the absence of detailed building and energy data, this process has remained somewhat arbitrary in UBEM research, relying on preexisting deterministic assumptions and the subjective judgement of the modeler about the correct values for model parameters. The resulting simplification can potentially lead to predictions that misrepresent urban demands and misinform decision makers. In individual building energy modelling, similar parameter uncertainty problems are typically solved through calibration techniques based on metered energy demand data [25,26]. Equivalent methods could be applied to UBEM, but very little research has focused on understanding how much accuracy could be achieved and how much building and energy data is required given its limited accessibility at this scale. This dissertation seeks to address the feasibility and accuracy of archetype-based UBEMs, in order to understand their potential to support urban decision making regarding energy demand and supply strategies for buildings.

## 1.2 Research hypotheses

The overall goal of this dissertation is to improve existing urban building energy modeling workflows to the point at which they can become decision support tools for those entities involved in the development and implementation of urban energy scenarios, from municipal governments, urban designers and utilities to the general public. Given the potential of these tools to provide actionable information to urban stakeholders as well as the challenges surrounding availability and access to data this work particularly focuses on the leadership role municipalities when it comes to collecting complete datasets of their jurisdictions and applying derived information for urban policy decisions.

Based on the shortcomings of existing methods described above, this translates into a more specific research goal: **to develop a methodology for the generation of calibrated archetype-based UBEM models, using building and energy data sources currently accessible at the urban scale**. This larger goal translates into the following three research hypotheses which will be addressed throughout this manuscript and revisited in the concluding chapter 7.

**Feasibility** (Chapter 3)

It is possible to generate and simulate a citywide UBEM and a library of building archetypes using available municipal urban datasets.

**Reliability** (Chapters 4-5)

Building archetype parameters can be calibrated by combining thermal simulation with Bayesian statistics, based on a subset of buildings for which metered energy demands are available.

The resulting calibrated UBEM can reliably reproduce building energy use intensity (EUI) distributions throughout a neighborhood, with more accuracy than a typical deterministic model.

The time resolution of the measured dataset determines the resolution at which the derived UBEM can provide reliable predictions.

**Relevance** (Chapter 6)

A calibrated archetype-based UBEM can be used in the analysis of policy and design scenarios, to provide actionable information for municipalities, energy providers and designers.

## 1.3 Dissertation overview

This dissertation presents the development of a methodology for the generation and calibration of archetype-based UBEM models, and their validation through modeling case studies in Boston, Kuwait, and Cambridge, of varying scale and context. *Chapter 1* has provided a brief overview of the scope of this work and its motivation, focusing on the relevance of urban energy modeling in current municipal energy planning. *Chapter 2* introduces the nascent field of Urban Building Energy Modeling (UBEM) to the reader in the context of exiting modeling techniques. A literature review of required data inputs, available tools and case studies is developed and current limitations for archetype-based UBEMs are identified.

*Chapter 3* introduces a workflow for the generation and simulation of UBEMs, based on urban datasets for buildings that are widely available for medium to larger US cities. As a case study, the workflow is used to generate a citywide model for the City of Boston in collaboration with the local planning department. Based on the case study, current limitations and barriers to the widespread use of these models are identified.

*Chapters 4 and 5* focus on the accuracy achieved through the use of uncalibrated and calibrated archetypes in UBEM. In Chapter 4, a Bayesian calibration approach for building archetype parameters is proposed and validated by comparing UBEM simulation results with annual metered data for a residential district tin Kuwait City. The effectiveness of the Bayesian approach to model EUI distributions is compared with that of two typical deterministic modeling approaches. In Chapter 5, the problem of calibration at lower temporal scales is discussed, and an expansion to the method is proposed if monthly measured energy use is available. The Bayesian approach is applied for monthly load analysis through the case study of residential archetypes in Cambridge, MA.

*Chapter 6* finally concentrates on the added value created with a calibrated UBEM, when applied in the analysis of future urban energy scenarios. Two example case studies are developed, based on the calibration results of previous chapters. Using the district UBEM created for Kuwait, three efficiency strategies and two electricity pricing scenarios are evaluated from the perspectives of a municipal energy planner, an energy provider and a policy maker. Next, two design proposals for a new residential neighborhood in Boston are compared in terms of total energy use and compliance with a local performance requirement, from the perspectives of an urban design team and a local planner.

The above three hypothesis are revisited in *Chapter 7* followed by a critical discussion of the advances made throughout this document as well as an outlook section that proposes concrete data and model management and implementation guidelines for municipalities interested in the use of bottom up urban building energy modeling to support their energy policy and planning efforts.

Chapter 2

# Urban scale building energy modeling

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The following chapter reviews the current state of the art of the nascent field of Urban Building Energy Modeling (UBEM). This particular approach is introduced in the larger context of energy modeling techniques, applied to large building stocks and individual buildings. UBEM data requirements and main current modeling workflows are reviewed thoroughly, and the "archetype" approach is discussed in detail. Model accuracy limitations are described in relation with archetype characterization methods, and a lack of validation and calibration studies is identified as a major gap in literature for the integration of UBEM in urban energy planning and decision making.

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*Elements of this chapter have been published in the Building and Environment Journal:*

*Reinhart CF, Cerezo Davila C (2016). Urban building energy modeling: A review of a nascent field. Building and Environment 97:196-202.*

## 2.1 Top-down vs bottom-up building stock modeling

As discussed in Chapter 1, municipalities and interested urban stakeholders need to better understand not only which sectors and buildings are responsible for current demands, but also what future effects comprehensive energy retrofitting programs and energy supply infrastructure changes might have. Over the last decades, the problem of predicting or estimating the energy demands of buildings has been addressed at two very different scales: The *building stock analysis* level, of interest for policy makers, and the *individual building design* level, relevant in architecture and engineering. Traditionally, urban energy models have inherited most concepts and techniques from the former. In that context, and to understand spatiotemporal energy demand patterns due to buildings, different types of urban modelling techniques have been proposed over time, which fall into two main classification categories (Figure 2-1): "top-down" or "bottom-up" models [11,27].

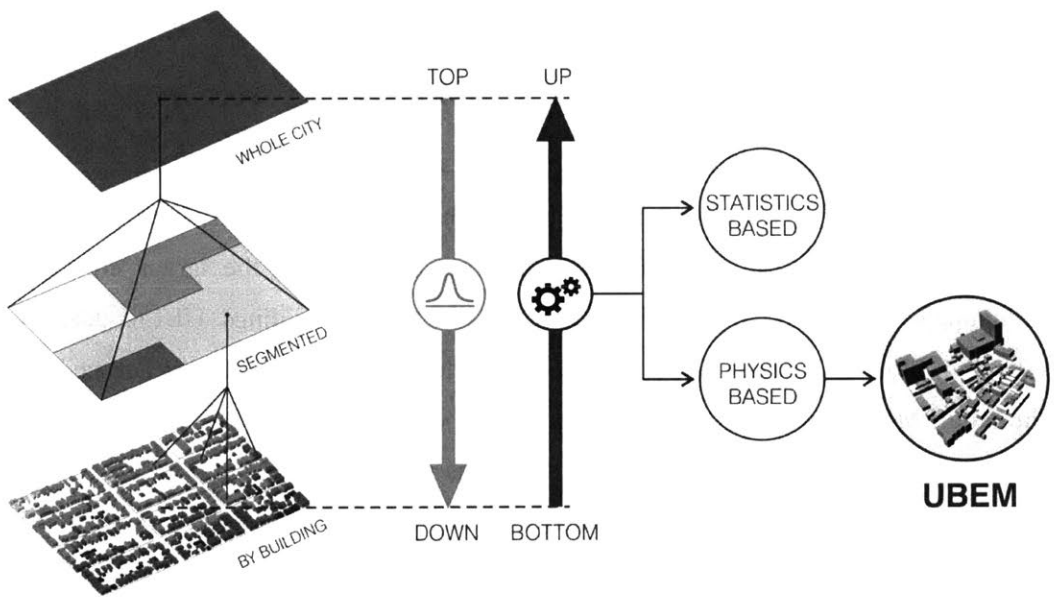


*Figure 2-1: Top-down vs bottom-up energy modeling methods*

The more general "top-down" models link aggregate urban energy use at the national, regional or urban scale to statistical variables, such as population trends and economic activities [12]. While useful for the understanding of larger existing stocks, they necessarily extrapolate from the status quo and are less suitable for the analysis of future energy supply-demand scenarios, where energy demands need to be characterized at the scale of the district or neighborhood. At this meta-scale, ranging from several dozens to thousands of buildings, "bottom-up" modeling techniques are better prepared to inform decision makers [13], and have been applied at national and urban scales in the past. "Bottom up" models apply statistical and/or "engineering" analytical methods to estimate the energy demands of each building individually.

Statistical models correlate available high level building parameters such as vintage, use type or size with individual building metered demand via regression models [28,29]. They are particularly "robust" when reproducing current individual building demands, since they are based on metered data and thus able to accurately incorporate occupant behavior, something notoriously difficult to accomplish in analytical models [30]. However, statistical models require large datasets of metered energy use, which are rarely available to modelers other than as annual data, and are unable to estimate lower temporal scales or forecast the impact of new technologies. To address these shortcomings, bottom-up "engineering" or "physics-based" models have been proposed where the demands of a building are estimated based on its specific properties (geometry, materials, systems, etc.) through analytical principle-based models [31].

Urban Building Energy Models (UBEM) [14] have been introduced as a more sophisticated family of engineering models, by applying performance simulation methods to represent each building as a dynamic thermal model, based on the same principles that govern individual building energy models (BEM) [15]. This relatively young field brings together the stock methods discussed so far with those of building performance simulation (BPS) used in architecture and engineering. UBEMs offer high flexibility to consider combinations of building technologies in future scenarios, and hence can be used by urban planners and policy-makers to evaluate impacts of potential retrofits or new construction, or to compare energy supply alternatives. Furthermore, they can be combined with grid models to evaluate the dynamic hourly performance of urban energy systems [32]. Although UBEMs are the focus of this dissertation, the same bottom-up simulation approach has been recently applied to the analysis of other urban sustainable performance criteria including material impacts [33], daylight access [34] or human mobility [35], as part of the field defined by Perez and Robinson as urban "micro simulation" [36].

## 2.2 Overview of Building Energy Modeling (BEM)

The basic approach of UBEM is to apply physical models of heat and mass flows in and around buildings to predict operational energy use. At the individual building level, such heat flows are well understood, and Building Energy Models (BEMs) are already widely used in many parts of the world for design, code-compliance and improved operation [15,37]. The purpose of BEMs, which belong to the larger field of Building Performance Simulation (BPS), is to simulate the effects of the environment in the indoor conditions of a space, due to envelope transmission loses, infiltration, ventilation and solar gains. Internal heat flows generated by occupants, lighting and equipment are also taken into account. Based on those BEM tools one can either estimate resulting changes in temperature and humidity in the space, or calculate the heating/cooling loads necessary to achieve a heat balance in which certain comfort conditions are maintained.

Since both the external climate and the internal conditions of a space change dynamically with time, significant research efforts have gone into the development of simulation algorithms capable of capturing their interactions, starting with the introduction in the late 60s of the "thermal response factor" method for modeling single rooms [38]. A first generation of "dynamic" BEM engines emerged in the seventies and eighties to overcome the shortcomings of early steady-state single room heat balance models. They applied computational heat transfer methods such as response functions or finite-difference methods to model the impacts of thermal mass in room temperatures. The eighties and nineties saw the integration of diverse, isolated modeling methods into the first whole building modeling tools. Multiple simulation engines have been introduced since, such as TRNSYS [18], ESP-r [17], DOE-2 [39], EnergyPlus [40] and IES-VE [41]. They have been validated against measurements in several example applications [40,42] and ANSI/ASHSRAE standards are in place to ensure their continued reliability [43]. An overview that contrasts the differences between them is given by Crawley et al [44]. Nowadays in the United States, BEM simulation is applied for energy code compliance following guidelines from the American Society of Heating Refrigerating and Air Conditioning Engineers (ASHRAE), through its Standards 90.1-2013 and 189.1-2011 [45,46]. Similarly, it is required for the fulfillment of energy-related credits in sustainability certification schemes such as LEED in the US [47] or BREEAM in the UK [48], where it is also used to show compliance with local building regulations.

In order to streamline the use of BEM engines in these scenarios, a variety of graphical user interfaces (GUIs) have become commercially available as part of modeling software packages such as DesignBuilder [49] or OpenStudio [50], simplifying the generation of multi-zone models. In a traditional usage case for these tools, an expert energy modeler is provided with building geometry, constructions, HVAC and internal loads data, as well as usage schedules for a building project. The level of available information is commensurate with the design stage of the project as building and occupant data is typically provided by the design or engineering team involved, sometimes requiring the modeler to make educated guesses for those parameters yet unknown. The modeler then enters the available information into the software in combination with weather data, a mostly manual, time consuming and costly process [51], and runs the simulation. More recently however, plug-in GUIs such as Archsim [52] or HoneyBee [53] have been developed to incorporate BEM into generic CAD modeling environments, making them accessible to architects and other non-expert users. This new approach to BEM tools, combined with the efforts of the American Institute of Architects (AIA) to actively promote the use of energy simulation in early design [54], has changed the traditional roles of architects and engineers in building performance design (BPD). New research questions are being explored as a result, regarding the effective integration of BEM in interdisciplinary workflows [55] and the education of non-experts users [56].

While the above outlined BEM process can in principle be applied to any new building to improve the energy efficiency of the built environment, the extent to which these methods are applied in practice is still low. To put it in perspective, while every year in the US between 80,000 and 100,000 new buildings are constructed, as of February 2017 there were only around 34,000 LEED certified. In that context, to become globally relevant, affordable, and reach a larger audience, the BEM field is shifting its focus towards the urban realm with the development of UBEM modeling.

## 2.3 Urban Building Energy Modeling (UBEM)

Bottom-up building energy simulation models, or UBEMs, reduce the dependence that statistical methods have on metered energy demand data, but increase the amount of necessary building information, hence introducing new modeling requirements. Since complete sets of building construction and usage information need to be generated and simulated for potentially thousands of buildings, conventional BEM approaches would become unacceptably resource intensive and impossible to manage. Therefore, in order to make UBEM an effective tool, a reconceptualization and automation of existing workflows is required. As documented in the review paper by the author covered in this chapter, a host of new methods had to be developed over the past decade in research to assemble and manage the enormous amount of data required to generate and ran an UBEM within a reasonable time frame [14]. These methods can be generally broken into the following subtasks: (1) Gathering and processing of data inputs, (2) generation and simulation of thermal models, and (3) result analysis and validation. The following sections explore in detail existing sources for each modeling step.

### *2.3.1 Data input processing*

An UBEM requires the combination of numerous datasets in order to characterize three main sets of inputs, shared by single building energy models (Figure 2-2): *Weather information*, *buildings geometry*, and *non-geometric model parameters* (Including data about constructions, systems, users, etc.). Climate datasets for building performance simulation have been available for a number of years following the initial establishment of a standard data format, the typical meteorological year (TMY) [57,58], and the subsequent provision of data available in this format for multiple regions worldwide (US-DOE EPW Data. URL: energyplus.net/weather). TMY files contain hourly measured environmental variables for a given site such as solar radiation, dry bulb temperature, relative humidity, or wind speed and direction. Apart from improving the world-wide coverage of these datasets, researchers have recently been exploring methods of how to model local microclimatic phenomena within cities such as the urban heat island effect (UHI) [59]. For the City of London, Mavrogianni et al coupled locally measured temperature profiles with a UBEM in order to study the impact of the UHI effect on building energy use and resident health [60]. Predicting local wind patterns [61] and linking IPCC climate change predictions to current day TMYs [62] are equally active areas of research with direct implications for UBEM. Although better modeling capabilities for urban microclimates are required, currently available data sources are sufficient for the analysis of annual or monthly demands in typical weather conditions, and accessible worldwide. Regarding building geometry data, an UBEM requires, as a minimum, 3D building shapes or "massings", information about the amount of façade openings, and terrain elevations when relevant. Depending on whether an existing or a new district is the subject of investigation, this information can either be extracted from available datasets or generated from scratch as part of an urban planning/design process.

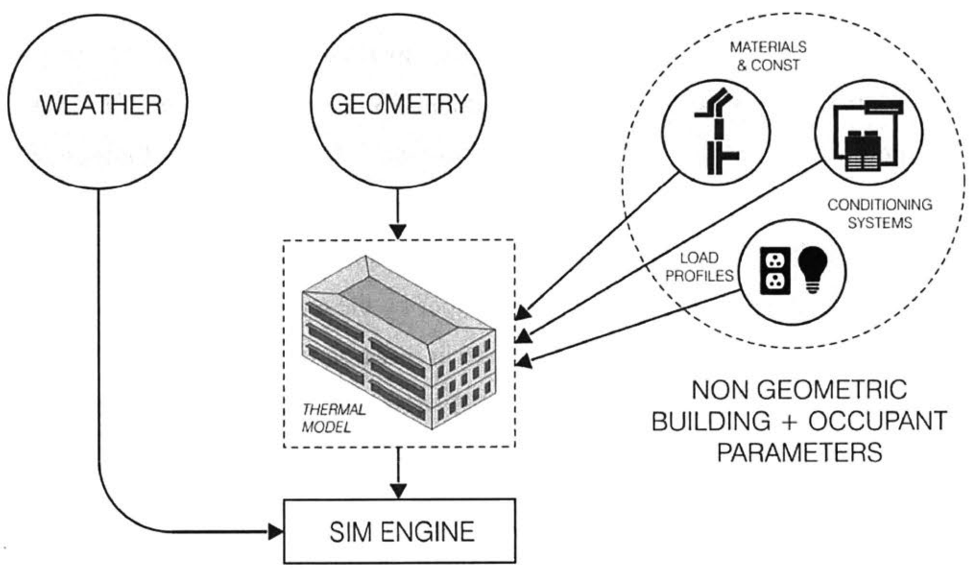


*Figure 2-2: Data inputs in UBEM modeling*

In the first scenario, a variety of urban sources with increasing level of detail have become available over time. Traditionally, two dimensional CAD files have been produced by municipal planning departments to document building footprints. Over the past decades, similar geometric data has been stored through city-wide Geographic Information System (GIS) databases, which have not only become commonplace in many regions of the world but are also increasingly accessible to the general public. GIS shape files can additionally store measured building and terrain height values, and be used to automatically generate the simplest form of massing through extrusion (Figure 2-3a), commonly referred to as a "2.5D" model [63]. Increasingly available LIDAR based datasets for cities, can allow for an even higher definition in building envelopes, capable of including smaller features such as sloped roofs or multi-height volumes [64], but at an increased processing cost. Finally, data formats such as CityGML offer yet a higher level of detail by combining complex 3D building models with a connected database [65], and are becoming a common source in urban modeling research in European countries [66–69].

In the case of urban design projects, 3D models with similar characteristics are routinely generated through CAD tools such as Rhinceros3D [70] or SketchUp [71], as shown in the example in Figure 2-3d which depicts an early proposal for Boston's Innovation District (Boston BPDA 2010). As far as the simulation process is concerned, geometric inputs are therefore identical for existing and new neighborhoods, and can be obtained with a justifiable effort level. Of all geometric inputs, façade openings are typically the hardest to model for existing neighborhoods, since municipalities do not collect data about their position and size, or even the ratio of the façade area they occupy, commonly referred to as a Window to Wall Ratio (WWR). To address this limitation, current research efforts are focused on developing methods for the automated identification of building openings from aerial or street photography through computational image processing methods [72].

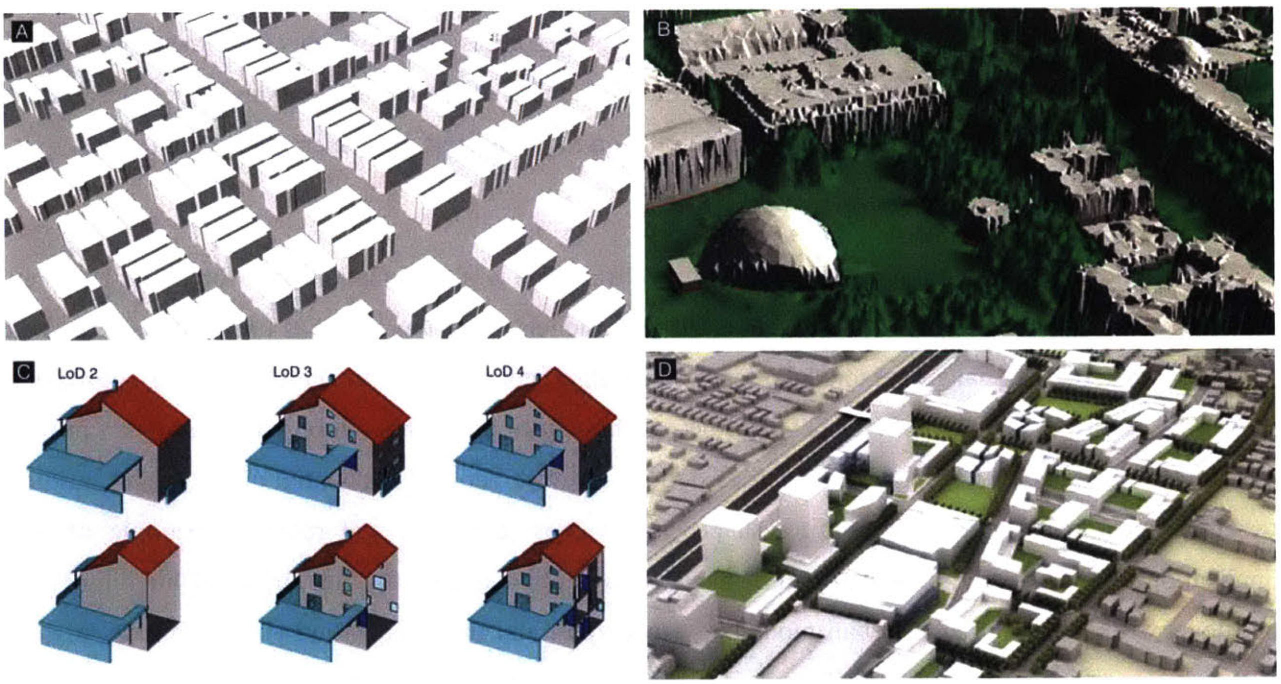


*Figure 2-3: GIS based 2.5D massing model (a), LIDAR based urban model (b), CityGML building LOD 3 model (c), and urban design massing proposal for the Boston BPDA (d)*

A third component, non-geometric model parameters have to be characterized as well, including material and construction information, HVAC systems' properties and operation regimes, and a long list of occupant related parameters. In a single building BEM, this step routinely takes about a third of the time spent preparing and creating a model [51] and constitutes one of the main sources of errors due to the unavoidable uncertainty regarding infiltration rates, usage schedules, occupancy rates, etc. [46]. While these quantities can be measured for a small group of existing buildings, such detailed data collection efforts become impractical for larger urban areas, and their characterization represents one of the largest challenges in UBEM. The most common solution to the lack of building data for all such parameters is the use of "building archetypes" i.e. average representations of a population of buildings assumed to share similar properties [23]. In their definition, buildings are usually classified based on properties such as age or use type, and then characterized according to representative parameter values for that group. As further described in the following section, developing this procedure can be very difficult given the natural complexity of the building stock in a city. The built environment is heterogeneous, and full buildings can rarely be described by single use categories, since they often accommodate multiple activities distributed in independently owned premises, which can be grouped in multiple ways for the purposes of energy metering. This is especially true for non-residential and mixed use building typologies. Similarly, uses within a building change through time dynamically, and a single structure can include multiple additions or renovations corresponding to different periods, which would require constantly revisiting its archetype definition. For these and other reasons, the use of archetypes necessarily influences the overall accuracy of the resulting model, as well as its ability to predict the impact of urban interventions or policies. Yet, it remains somewhat arbitrary and deterministic, relying on the subjective judgement of the modeler.

### *2.3.2 Archetype modeling*

As introduced above, building archetypes in UBEM are a simplification tool for assigning non-geometric simulation parameters to individual building models. This approach has been extensively used in the context of national or regional bottom up building stock models to understand the aggregated impact of energy efficiency policies [31] and new technologies [23]. The still ongoing European project TABULA, in which 13 EU member countries defined relevant national residential archetypes according to climatic zone, vintage and building shape, is the most complete and relevant example of this application [73]. However, such national databases are rarely available for the variety of building types and level of detail required in urban modelling archetypes, and their generation and validation process still remains one the most undefined steps in UBEM. The definition of a set of archetypes is typically developed in two steps: *Classification* and *Characterization.* In previous urban modeling research, these steps have been developed to the extent that available data sources allowed.

#### Archetype Classification

In *classification* (Or *segmentation*), buildings are grouped according to one or more indicators which need to be: First, correlated to the energy demand of the building (e.g. building use as an indicator can convey when it is occupied) and second, available for all buildings. This second condition typically limits the number of indicators since few energy variables are documented throughout a city's building stock. The indicators most often used to classify buildings into archetypes are programmatic use (e.g. residential, office, retail, etc.), floor area, shape typology and age of the construction [24,30,74–81].

These four indicators are readily available in most municipalities as part of property datasets, but fail to capture the complexity of the building stock especially in the case of mixed-use buildings, in which the floor area dedicated to specific uses is rarely available. Smaller spatial classification scales have been proposed to represent sections of one or multiple buildings with one or more distinct uses such as the Self Contained Unit (SCU) [82], which can be used to better align the model with the real spatial configuration or distribution of energy meters. Additional indicators have been proposed to complement these, such as household demographics [83], heating system [77] or window to wall ratio (WWR) [72].

*Table 2-1: Number of buildings and archetypes in published studies*

| Scale of Application | # Bldgs.* | Use Type | Classification Parameters | # Archs. | Characterization Method | Bldg./Arch. Ratio | Ref. |
|---|---|---|---|---|---|---|---|
| Urban (Osaka) | 1,128 | Residential | Shape/Area | 20 | Virtual | 56 | [83] |
| Urban (Houston) | ** | Mixed | Shape/Age/Use/System | 30 | Virtual | ** | [79] |
| Urban (London) | 267,000 | Residential | Shape/Age | 144 | Virtual | 1854 | [30] |
| Urban (Carugate) | 1,320 | Residential | Age | 7 | Sample | 189 | [23] |
| Urban (Milan) | ** | Mixed | Shape/Age/Use | 56 | Virtual | ** | [74] |
| Urban (Rotterdam) | 300,000 | Residential | Shape/Age | 26 | Virtual | 11,538 | [75] |
| Urban (Several US locations) | 200<br>33,000<br>200,000<br>15,000 | Mixed | Shape/Age/Use/System | 12<br>37<br>17<br>25 | Virtual | 17<br>892<br>11,765<br>600 | [81] |
| Urban (Basel) | 20,802 | Mixed | Shape/Age/Use | 20 | Virtual | 1040 | [85] |
| National (UK) | 115,751 | Residential | Shape/Age | 47 | Virtual | 2463 | [31] |
| National (Italy) | 11,226,595 | Residential | Shape/Age/Climate | 96 | Sample | 116,943 | [24] |
| National (Greece) | 2,514,161 | Residential | Shape/Age/Climate | 24 | Sample | 104,716 | [76] |
| National (Greece) | 2,514,161 | Mixed | Shape/Age/Use/System | 5 | Virtual | 502,832 | [86] |
| National (Italy) | 877,144 | Residential | Shape/Age/Climate/System | 3168 | Virtual | 277 | [78] |
| National (Ireland) | 40,000 | Residential | Constructions/Thermal | 13 | Virtual | 3078 | [84] |
| Regional (Sicily) | 171,000 | Residential | Shape/Age/Climate | 84 | Virtual | 2036 | [77] |
| National (France, Spain, Germany, UK) | 14,916,600<br>9,804,090<br>18,040,000<br>20,496000 | Residential | Shape/Age/Climate/System | 92<br>120<br>122<br>252 | Sample & Virtual | 162,137<br>81,700<br>147,869<br>81,333 | [87] |
| National (Finland) | 36,000 | Mixed | Age/Use | 12 | Sample | 3000 | [80] |

* Number of buildings to be represented by archetypes. ** Number of buildings not available in the study.

Measured energy demand by individual building, for sufficiently representative sections of the urban stock, can significantly improve the classification process, helping identify statistically those indicators with the strongest correlation [28,84] or clarify their meaning. For example, Aksoezen et al. [85] used measured gas consumption data from 1,356 meters to test the common assumption that building age is a good classification indicator since the older the building the higher its demand for heating. The authors showed that in fact, buildings constructed in the period of 1921 to 1979 used more gas than those built before or after. Unfortunately, UBEM modelers do not usually have access to sufficient measured energy demand for individual buildings, and there is no way to validate the effectiveness of the chosen classification indicators. As a result, no consistent relationship between the size of an UBEM and the number of archetypes developed has been so far established. Classification indicators and number of archetypes are typically chosen based on already existing categories, and complex situations such as mixed-use buildings or structures with multiple additions, which cannot be described through simple indicators, are usually excluded from the model. The extensive review of published building stock modeling efforts by the author showed that [14], depending on the scale of application and indicators chosen, an archetype may represent 50 to 500,000 buildings (Table 2-1, Figure 2-4).

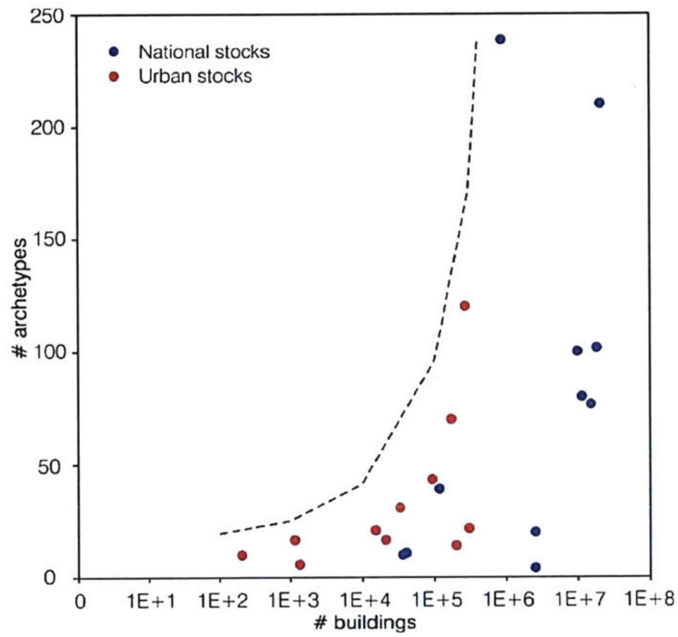


*Figure 2-4: Ratio between number of buildings and archetypes in reviewed studies*

<u>Archetype Characterization</u>

Once all buildings in an urban model have been *classified*, each resulting archetype has to be *characterized* for all relevant energy simulation parameters. These are all non-geometric building and occupant factors which influence energy demand, including envelope construction details, HVAC system properties, occupancy schedules, internal loads, etc. The exact set of parameters to be defined depends on the UBEM simulation tool, the thermal modelling approach (steady state vs dynamic) and the model zoning simplification (single zone vs multi zone) [14]. For a given parameter combination however, defining their values in an urban modeling setting is a particularly complicated task. The most common approach is to characterize archetype parameters in a *deterministic* way (i.e. a single value assigned to each parameter and used for every building). This can be achieved either by assigning to the archetype the characteristics of an audited *real building* belonging to it, or of an average *virtual building* [24]. Table 2-1 shows the selected approach for a variety of published modeling studies.

Both approaches have the limitation that, even if the archetypical building correctly represents the mean or the median of all buildings in its group, individual buildings will perform differently. For example, two "midsize offices from the 1980s" will have distinct working hours or glazing types which are unknown to the modeler. Archetype descriptions that use solely deterministic parameters are thus intrinsically unable of reproducing the diversity of demands found within the population they represent. Therefore, to account for this variety and for the modeler's uncertainty regarding specific buildings, they can also be characterized in a *probabilistic* way, using distributions [68]. The use of uncertainty modelling techniques to deal with unknown parameters has been extensively addressed in BEM for retrofit and design purposes [88,89]. However, it remains unclear how to effectively apply these methods at the urban level, where they are limited by the lack of parameter data and the high computational cost of simulation. For that reason, most existing UBEMs have so far relied on deterministic characterization, at a detail level commensurate with available data sources. What are these sources?

In the simplest case, values used to characterize archetype parameters can be extracted from *literature data*, such as national building surveys, building codes and standards, and research literature. In the United States for example, the largest databases of energy related building characteristics are the Commercial and Residential Buildings Energy Consumption Surveys (CBECS/RBECS) published by the US Energy Information Administration [90,91]. They have been used for the definition of urban archetypes [79,92] in combination with current and historic ASHRAE energy efficiency standards [45] and reference building models published by the US Department of Energy [93]. Similar resources can be found in most countries, and in Italy for example, Caputo et al. [74] divided both residential and commercial buildings in Milan, into 56 archetypes, characterized using the Italian National Census. Although literature sources are a valid starting point, sometimes more granular *building data* is available which can provide characteristics of individual buildings within the urban area being modelled. This requires the modeling team to audit or survey a sample of buildings for selected archetypes [23,81], or to work in collaboration with local companies or institutions which may have performed them in the past [30]. In large enough samples, building audit data can also serve as a basis for a probabilistic characterization, providing empirical distributions for parameters. Unfortunately, given the cost and labor required to develop building by building surveys, such datasets are uncommon and limited in coverage. The introduction of mandatory building Energy Performance Certificates (EPCs) in the European Union [94] has been proposed as a potential solution to the problem [95], but no equivalent initiative is currently underway in the United States. Hence, the question remains, what might be an effective way to introduce probabilistic archetype parameters in large scale UBEMs?

### 2.3.3 Thermal simulation methods and tools

Once climate data, building geometry and archetype templates are available, they need to be combined into a thermal model, and divided in zones than can be analyzed in a simulation engine. Previously published UBEM workflows mainly differ in the type of simulation, the detail of thermal zoning used, as well as whether the effect of surrounding buildings is taken into account (Table 2-2). A number of these workflows are described in the following, going from low to increasingly higher complexity. In the simplest case, an UBEM consists of single zone, steady state heat balance models of a sample building for each archetype. Simulation results are scaled up to the ensemble level by multiplying them with either the number of buildings per archetype [31] or a floor area-weighted function of that number [23]. This modeling approach ignores that the urban context and specific shape of a building can significantly affect its performance e.g. through shading, local wind patterns, etc.

To consider shading as well as building compactness the SIMSTADT tool in combination with the INSEL simulation engine applies a single-zone steady state model to each building separately [66,68,69,96]. While steady-state methods are generally known to reliably predict heating loads, dynamic thermal simulation engines such as EnergyPlus [16,40] and DOE2 [39] are preferable for locations with notable cooling needs, or where hourly demands are especially relevant. Mata and Caputo accordingly used context-less single zone dynamic models to analyze archetypes in France, Germany, Italy, Spain and the UK [74,87]. Last, for investigations of detailed urban design choices, multi-zone dynamic thermal models may become necessary, which can capture demand variations resulting from different solar exposures. In practice, this requires converting a massing model into a network of volumetric thermal zones. Same as for single zone models, multi-zone models can either be generated for sample buildings only [19,75,79] or for each building individually so that solar shading can be considered as well [97].

*Table 2-2: Thermal modeling methods*

| Type of Thermal Model | Type of Simulation | Context Modeling | References |
|---|---|---|---|
| Single Zone | Steady State | No | [23,31] |
| Single Zone | Steady State | Yes | [63,67,96] |
| Single Zone | Dynamic | No | [87] |
| Single Zone | Dynamic | Yes | [98] |
| Multi Zone | Dynamic | No | [19,79,99] |
| Multi Zone | Dynamic | Yes | [97,99–102] |

While simple steady state simulation models for several thousand buildings can be executed in a matter of an hour on a standard laptop, the simulation time for equivalent dynamic multi-zone models may take days, even when parallel or cloud computing resources are available. In addition, building floorplans are not available to modelers at an urban scale. For both reasons, massings in a multi-zone UBEM need to be simplified depending on acceptable simulation times and purpose of the model (Figure 2-5). In the simplest case, each floor of a building can be treated as a zone, to capture vertical solar exposure variations in a dense urban context [92]. To further capture the impacts of orientation and building depth, building floors can be divided into core and perimeter thermal zones, as recommended by ASHRAE 90.1 Appendix G [45]. To apply this operation to any geometric form, Dogan et al [103] developed an "autozoner" algorithm which automatically generates ASHRAE 90.1 compliant models from massings. While effective, the core and perimeter approach can result in an excessive number of simulations for a neighborhood or district. To maintain accuracy while reducing the number of simulations, less resource intensive approaches have been recently proposed such as integrating reduced order models [104], aggregating internal zones into thermal mass elements [105], clustering building envelope zones with similar exposure conditions into shoebox models [22] and others [106]. When choosing a simplification, floorplan typologies can become relevant, since core and perimeter schemes can misrepresent the thermal behavior of real spaces with errors up to 70% [107].

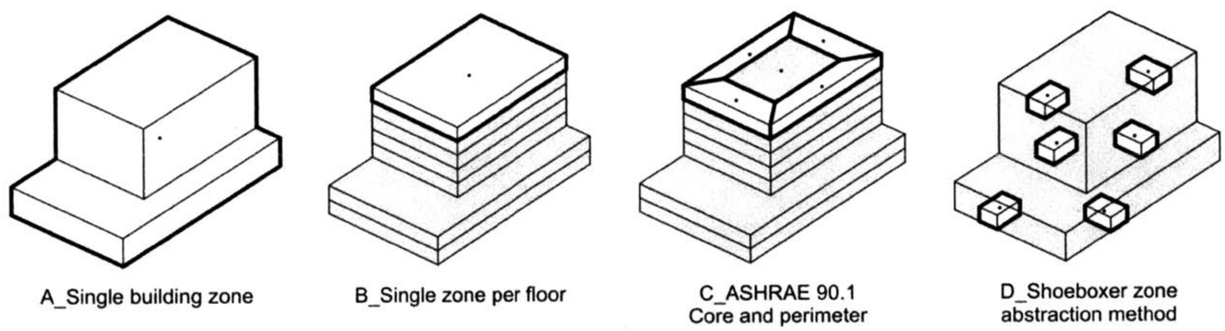


*Figure 2-5: Thermal zoning approaches for 3D massings in UBEM*

The processes of integration of data inputs, execution of the simulation itself, and communication of results back to the user, have been implemented in the past with varying levels of automation. In most cases the developers combined export/import capabilities of exiting tools such as GIS and BIM as well as custom scripts to generate a thermal model, execute the simulations and present them via spreadsheets or GIS applications [19,23,30,75,99]. A few groups further automated and streamlined the simulation workflows to incorporate additional urban performance metrics and make UBEM accessible to urban designers and planners: SUNTOOL [102] and the CITYSIM [100] are examples that combine a custom GUI with newly developed thermal simulation engines. While data inputs are manually defined CITYSIM, SIMSTADT for example can automatically read a CityGML database [68,69,96]. In a further step in user interface development, the Urban Modeling Interface (UMI) developed at MIT works as a plug-in for the CAD modeling software Rhino, which allows developing parametric 3D urban models, exporting and executing them in EnergyPlus, while also offering daylighting, lifecycle and mobility analysis [97]. Using a similar plug-in approach, an integrated UBEM tool for ArcGIS was developed at the ETH Zurich, capable of producing results at multiple spatial and temporal scales [98].

As a final step, UBEM results have to be reported back to the user in spatial and/or temporal form (Figure 2-6). A majority of existing tools offer capabilities to produce false colored energy maps and export or visualize time series results [69,98,100,102,108]. Taking a step further, Giovannini et al explored the connection of archetype databases and CityGML 3D models with web visualization techniques in the SUNSHINE project [109]. These or any UBEM visualization tools face the challenge of communicating massive amounts of energy data to urban stakeholders as actionable information, which falls under the exponentially growing field of "big data", outside of the scope of this literature review.

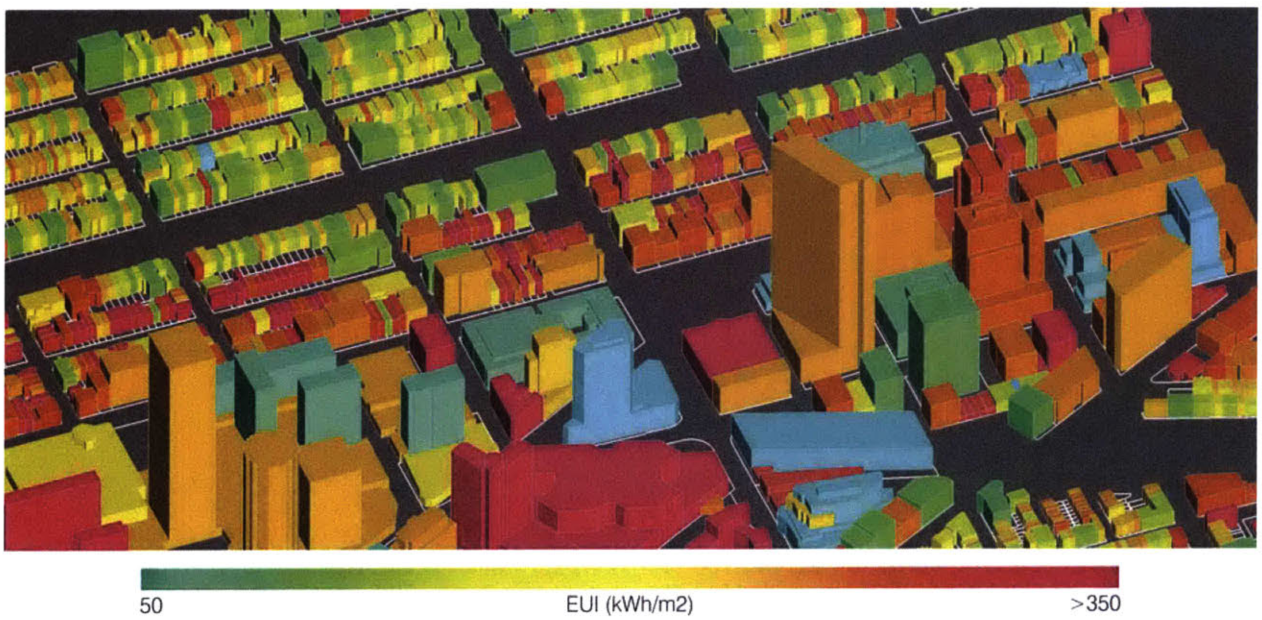


*Figure 2-6: Heat map of UBEM simulated demands in Boston's Back Bay district*

As described previously, multiple viable workflows have been proposed in the last decade for the generation and simulation of UBEMs for urban energy planning purposes, and tested in a variety of well documented research case studies. However, for any of such workflows to become an effective tool for municipalities or urban decision makers, viability is not enough. It has to be possible for an urban modeler to create and maintain an UBEM, using currently available citywide datasets and data management practices, with a justifiable effort. To the author's knowledge, no previous research project in the field has directly worked with a municipal planning team to identify the possibilities and limitations of such datasets, and bring UBEM into real practice.

### 2.3.4 Model accuracy and validation

The ability of UBEM models to support different design or policy decisions naturally depends on how reliable the simulation results actually are. Given that even individual BEM predictions may significantly differ from measured results due to uncertainties such as infiltration rates and occupant behavior, it may initially seem unlikely that an UBEM will be capable of faithfully predicting the energy use of many buildings. However, when comparing *aggregated* annual measured versus simulated energy use of multiple buildings, these individual model inaccuracies tend to average out, resulting in reported errors ranges between only 5% and 20% for heating loads [23,69,77,101] and 1 and 19% for total Energy Use Intensity (EUI) [74,79,83,98] (Table 2-3), errors levels fairly close to the maximum allowed in individual BEMs according to ASHRAE Guideline 12-2002 [110].

*Table 2-3 Validation reported error simulated*

| City/Region | # of Measured Buildings* | Simulation Outputs | Validation Scale | Reported Error Range | Reference |
|---|---|---|---|---|---|
| Osaka | 1,128 | Total EUI | Aggregate | 18% | [83] |
| Houston | ** | Total EUI | Aggregate | 10-13% | [79] |
| Carugate | 1,320 | Heating | Aggregate | 10% | [23] |
| Milan | ** | Total EUI | Aggregate | 4% | [74] |
| Sicily | ** | Heating | Aggregate | 8% | [77] |
| Los Angeles | 27 | Total EUI | Building | 11-23% | [99] |
| Thessaloniki | 4 | Heating | Building | 12-55% | [86] |
| Ludwigsburg<br>Karlsruhe | 35<br>22 | Heating | Aggregate / Building<br>Aggregate / Building | 21% / 5-50%<br>7% / 18-31% | [69] |
| Freiburg | 22 | Heating | Building | 1-60% | [105] |
| Navy Yard<br>Arlington County | 200<br>6 | Total EUI | Building<br>Building | 5-69%<br>5-50% | [81] |
| Swiss Village | 100 | Heating | Aggregate / Building | 8%/ 6-88% | [111] |
| Swiss District | 22 | Heating<br>Total EUI | Building<br>Aggregate / Building | 9-66%<br>1-19% / 8-99% | [98] |

* Number of buildings with measured energy use. ** Number of buildings not available in the study.

These error ranges are acceptable for guiding decisions that affect multiple buildings. However, for a peak load analysis, which usually focuses on aggregate hourly load profiles, differences of up to 40% were reported by Heiple and Sailor [79]. As one would expect, simulation accuracy decreases as results are analyzed at the individual building level, with reported error ranges of 12 to 55% for regional stock models and 5 to 99% for urban models. While detailed UBEMs can reduce errors related building shape, urban context and solar radiation, the use of archetypes introduces additional simplification errors. When archetype parameters are characterized deterministically (e.g. one single value for all buildings within it) through an average or typical value, they necessarily misrepresent the diversity of envelopes, systems and especially occupant behaviors. In the case of probabilistic approaches, there is rarely enough building data to characterize uncertainty distributions. In individual building modelling, equivalent parameter uncertainty problems are typically solved through calibration methods based on metered energy consumption data. However, very little research has focused on developing UBEM calibration methods and understanding how many buildings metered energy use is required and at what time resolution.

## 2.4 Conclusions

The preceding sections have described how UBEM techniques have been introduced in the last decade as a hybrid application from the fields of building stock analysis and building performance simulation. Significant progress has recently been made towards the development of simulation workflows to implement UBEMs, taking advantage of a variety of data sources and thermal modeling techniques. Given the insight that municipalities and other urban stakeholders may potentially gain from such tools for planning, design and policy decisions, the required effort level seems justifiable.

Yet, for UBEM to distinguish itself as a reliable urban planning tool, several challenges remain to be addressed. The largest remaining limitations for UBEM are associated with the definition of archetypes that reliably represent the properties of the urban building stock in a model. As with the case of building geometry and thermal zoning, a certain level of simplification is unavoidable when characterizing buildings at this scale. However in the case of archetypes, as presented in section 2.3.2, no clear relationship has been established between number of archetypes, size of a model, and resulting accuracy, with a single definition being used to represent from tens to thousands of buildings. Furthermore, no previous research has tried to quantify the uncertainty or error introduced in the model resulting from the classification and characterization of archetypes, a process which remains deterministic and somewhat a hoc, relying on the subjective judgement of the modeler.

UBEM archetype parameters, especially those related to occupant behavior, require the implementation of stochastic uncertainty modeling methods in order to reproduce the real diversity of energy demands found in the built environment. Unfortunately, due to tightly restricted access to measured energy use, as well as generally insufficient knowledge of the characteristics of buildings and occupants, it is often impossible to quantify or model such uncertainties. To tackle this problem, modelers require access to building, occupant and energy data for representative buildings. Some city and state governments, which represent a key stakeholder group for this type of work, have already passed ordinances that require energy use of select building types to be made public, such as BERDO in Boston [9]. However, there is still a large way to go in terms of data availability.

As a result of the referred limitations in the definition of archetypes and the access to energy data by building, few studies have focused on improving the accuracy of UBEM models when compared with metered demands through calibration. The handful of validation studies available, reviewed in section

2.3.4, showed that while models involving of larger groups of buildings showed good agreement with measurements in the aggregate and average levels (errors below 15%), simulation errors greatly increased for individual buildings. This is the unavoidable result of using deterministic archetypes to represent a diverse population of buildings. However, it seems unreasonable to expect urban modelers to not use archetypes and instead characterize each buildings individually, especially when both the building and its users will change multiple times in the long term for which urban decisions are made. For that reason, in combination with the use of stochastic archetypes, specific calibration techniques need to be proposed to allow UBEMs to accurately represent not only the aggregate but also the diversity of building energy demands in a district or neighborhood.

Even if previously discussed issues of archetype and model accuracy were to be solved at a theoretical level, UBEMs will have no impact in urban decision making until they can be created and applied in practice by municipalities. This will first require the adaptation of UBEM modeling workflows to the datasets and formats currently used in practice and maintained by municipal governments. A majority of currently available UBEM workflows have been developed in research for the analysis of well documented case studies, but have not addressed the challenges that arise when scaling up those methods to the scale of a complete city. There is hence a need for researching how UBEM workflows have to adapt to these circumstance, and/or how municipalities will have to change their practices to make modeling feasible with an acceptable effort level. Finally, in order for UBEMs to have the larger societal impact that was envisioned in the introduction, stronger intellectual engagement between planners, policymakers and the building modeling community is necessary. This will require training a new generation of individuals, who understand in which decisions and at which scales the use of UBEM is appropriate. However no research in the field has so far focused on defining conditions for the use of UBEM from the perspective of potential interested urban stakeholders. The following chapters of this dissertation propose solutions for some of the key shortcomings that have been identified above.

## 2.5 Summary

The previous sections developed an extensive review of the field of Urban Building Energy Modeling (UBEM) and existing challenges for its effective implementation in practice. The key findings of this literature review are:

- UBEM modeling is a nascent field that combines building stock analysis with building energy simulation techniques for the estimation of energy demands.
- UBEMs require extensive data inputs including weather information, building 3D massing geometry, and non-geometric model parameters typically applied as “archetypes”.

- No relationship has been established between the number and detail of archetypes, and the accuracy of an UBEM.
- Current deterministic archetype characterizations achieve low errors when estimating aggregate urban demands, but fail to capture the diversity of demands found in individual buildings.
- No method has been proposed for the introduction and calibration of stochastic model parameters in archetype-based UBEMs.
- No UBEM has been implemented at a citywide scale using only currently available and maintained data sets and practices.

Chapter 3

# Feasibility and limitations of citywide UBEM

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This chapter evaluates the feasibility of generating citywide UBEM based on data sets that are available for many cities worldwide. The author collaborated with the Boston Planning and Development Authority (BPDA) to develop a model for the city, for purposes of energy supply planning. An automated GIS to UBEM workflow is developed in the following sections, and implemented to generate energy models for 83,541 buildings based on 52 use/age archetypes. The buildings are then simulated using the US DOE EnergyPlus simulation engine, and average results for buildings of the same archetype are compared against data from the US national energy consumption surveys. The modeling barriers of current urban datasets and required effort level are evaluated through the process. The lack of widely available archetype templates and metered energy data, as well as the lack of standardization in building databases, were identified as key limitations that may impede cities from effectively applying UBEMs.

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*Elements of this chapter have been published in the Energy Journal, and the proceedings of the IBPSA International Conference:*

*Cerezo Davila C, Reinhart CF, Bemis J (2016). Modeling Boston: A workflow for the efficient generation and maintenance of UBEMs from existing geospatial datasets. Energy 117:237-250.*

*Cerezo Davila C, Dogan T, Reinhart CF (2014). Towards standardized building properties template files for early design energy model generation. 2014 ASHRAE/IBPSA-USA Building Simulation Conference, 10-12 September, Atlanta GA.*

## 3.1 Introduction

All recent advances in urban modeling techniques discussed in Chapter 2, suggest that UBEMs may become a useful tool for city officials, urban planners and energy providers around the world. However, the review also highlighted the complexity of available modeling workflows, both in terms of the multitude of datasets required and the variety of computational tools involved. While this level of complexity can be managed in controlled research exercises, it necessarily raises concerns about the feasibility of UBEM workflows in practice. As of today, is the average municipality technically prepared to build its own UBEM for energy planning and policy?

This chapter centers on understanding the necessary steps to generate a viable citywide UBEM using the city of Boston as a case study. As part of its Greenovate Climate Action plan [9], Boston has committed to significantly reduce its GHG emissions through a variety of demand and distributed generation strategies. In this context, the author collaborated with the Boston Planning and Development Authority (BPDA) on the development of a model for building demand estimation using UBEM. Its results were later used by MIT Lincoln Lab to develop supply scenarios for various parts of the city [14]. To ensure that the workflow would be readily replicable in other cities in the US and elsewhere, the study focused on identifying the minimum data requirements and how they compare with the information about buildings that an average municipality might have available. While neighborhood or district UBEMs have been generated as research exercises [96,98], no model of comparable size with individual dynamic simulations per building had been developed within a municipal department at the time of writing.

The goal of this chapter is to confirm the "Feasibility" research hypothesis proposed in the introduction, and to do so three main research objectives are addressed in the following sections:

- To test the feasibility and effort level of generating a viable citywide UBEM based solely on currently available urban datasets in US cities.
- To identify logistic and technical barriers within existing urban data workflows that may prevent cities from setting up and maintaining an UBEM.
- To assess the level accuracy of said UBEM when no calibration data is available.

## 3.2 Methodology

In order to answer the previous research objectives and analyze the feasibility of citywide UBEMs, a methodology is proposed, which requires to: (1) Identify the extent of standard and widely available urban datasets regarding buildings, (2) Define based on them the minimum viable UBEM, (3) Create and implement a toolset for its generation, and (4) Document modeling limitations in each step. These four activities were developed in the definition of a modeling workflow for Boston, as an example representative of a typical US large city. Based on previous studies described in Chapter 2, three main tasks can be defined as part of an UBEM modeling workflow: *Characterization*, *generation*, and *simulation*. Each one of them was implemented to the extent that available data sources allowed. The following sections describe that implementation:

### *3.2.1 Data availability and model characterization*

This task includes the analysis of available data sources, and the characterization of the three basic datasets referred in Chapter 2: Weather information, building and context 3D geometry, and building archetype parameters. The first is the least problematic in terms of data gathering. TMY weather files in EPW format are publicly available for most large cities in the US and maintained by the Department of Energy, hence becoming the standard for both BEM and UBEM modeling. However, for other areas of the world or remote/small US towns, additional efforts might be required in their production, relying on local weather stations or geographic interpolation of existing datasets. For this study, the TMY3 file for Boston Logan Airport, which is located along the Atlantic coast directly northeast of the city, was used for all simulations. In the case of Boston, it has previously been shown that variations in annual building energy use caused by urban heat island phenomena across the larger metropolitan area amount to 8-10% when compared with the airport TMY3 file [112]. While it is in principle possible to model such effects [113], the author decided against adding this level of complexity to the model, since no streamlined tools have been so far developed for their application.

Building related data inputs (geometric and otherwise) are more problematic. The extent to which they can be defined depends on the information currently stored by municipal departments and its accessibility. As opposed to TMY weather data, building information is not stored for its use in energy modeling, nor is it standardized in any particular format. In fact, in most US cities the data is spread throughout several databases built for separate purposes of property tax assessment, zoning code compliance, or urban visualization. Since some of them might not exist in a digital format, UBEM workflows are limited to those already integrated in a centralized data system. In US municipalities, Geographic Information Systems (GIS) have assumed that function becoming common place in urban planning departments over the past decade.

A technically sophisticated city the size of Boston typically employs a dedicated GIS department that centrally maintains a digital dataset of all city assets. Furthermore, GIS data is typically made available to the public through open data portals such as the Boston Data site (URL: data.cityofboston.gov) or the New York DoITT (URL: www1.nyc.gov/site/doitt/). Because of this institutional presence, city employees are familiar with GIS related tools and new plans for urban development tend to be designed in compatible environments. Minimum entry fields in such databases are parcel and building footprints, as well as building height, embedded in GIS shapefiles which combine geometry and data tables. Often, a complementary "tax assessment" database will include data about use types, floor area, assessment value and the dates of major renovations. Given their flexibility for storing geometry and data, and the effort level that goes into maintaining these datasets they constitute a natural data source for citywide UBEMs, and the de-facto standard for urban data management. As described in Chapter 2, the CityGML data format has been proposed as a more appropriate framework for urban energy modeling [114], but it is still not available is most US cities, with the exception of New York which maintains a CityGML datasets for its buildings in level of detail 1 and 2 (URL: www1.nyc.gov/site/doitt/initiatives/3d-building.page).

While GIS provides a useful framework to organize available information, building related fields are limited in number, heterogeneous in format, and rarely contain information about key energy-related parameters such as insulation levels, heating/cooling systems or operations schedules. This means that a field mapping procedure is necessary, usually through the use of "lookup" tables, in order to link variables from a city's GIS database to UBEM input parameters or archetype classification indicators. Formulating it requires a detailed understanding of the meaning of existing data fields as well as some creative thinking about how to treat those missing, incomplete or not available at the building level. Since this mapping is a onetime task, cities can rely on an expert consultant to perform this step, but they need to be involved in the process. The specific mapping used for Boston is explained in the following.

Data mapping and processing

A basic GIS database for buildings includes three datasets common and available in most US cities: Building footprints, parcel geometry, and property tax assessment. In the 2014 Boston municipal database, spatial information includes polygon type shapefiles for parcels (PRC) and building footprints (BLD), as well a point type shapefile for "lite" tax assessment records (TXP). In addition, a "full" dataset of tax records for each property for the 2014 fiscal year (TXR) was provided as a text file to complement the lite dataset. As part of TXR, look-up tables were provided associating property type use codes (PTYPE) with the use name. These datasets had to be connected so that available information could be attributed to individual buildings throughout the city. Table 3-1 summarizes the datasets used in the model and the building parameters selected, while Figure 3-1 shows their spatial relationship.

*Table 3-1: Original datasets and selected data fields for the Boston UBEM*

| Dataset (CODE) | Data Type | Unique Key | Selected Data Field | Original Field Name |
|---|---|---|---|---|
| Tax Parcels FY14 (PRC) | GIS Shapefile | PID_PARCEL | - | - |
| Building Footprints (BLD) | GIS Shapefile | None | Roof Elevation<br>Ground Elevation<br>Structure Type<br>Building Land Use Code | ROOF_ELEV<br>GRND_ELEV<br>IEL_TYPE<br>BRA_LAND_U |
| Property Tax Record Lite (TXP) | GIS Shapefile | PID | Condominium Id<br>Parcel Id<br>Land Use Code<br>Property Type Code<br>Max Number of Floors | CM_ID<br>PID_PARCEL<br>LU<br>PTYPE<br>NUM_FLOORS |
| Property Tax Record Full (TXR) | Database Table | PID | Year Built<br>Year Remodeled<br>Structure Type | YEAR_BUILT<br>YEAR_REMOD<br>STRUCTURE |
| | | | Residential Info<br>Condominium Info<br>Condo Unit Info | *Various fields including number of rooms, façade finish, presence of AC, etc.* |

In Boston, the most detailed property data is defined at the scale of the parcel. Existing information is associated with a tax identification number (PID) corresponding to a point within the TXP dataset and a record in the TXR. In addition, each point is also associated with a parcel identification number (PID_PARCEL) which refers to the specific parcel and address it belongs to within PRC (Figure 3-1). In most cases, when there is a single property owner within the parcel, both PID and PID_PARCEL codes will match. However in the case of condominiums where multiple owners exist in a parcel, a third id number (CM_ID) is defined that matches the id of the parcel. Geometric information such as building elevation, ground elevation and footprint are associated with the BLD dataset which has no common unique id with the PRC dataset. In BLD one or more polygons are defined within a parcel, with each one representing a complete or partial building footprint plus building elevation.

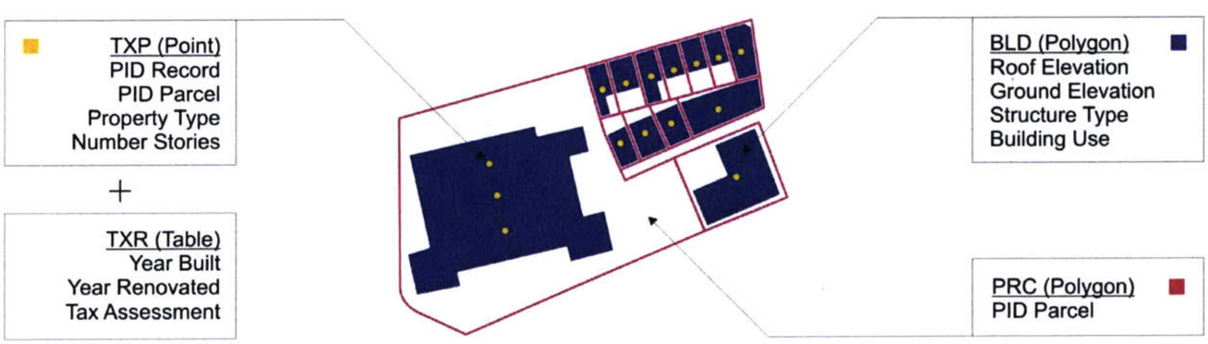


*Figure 3-1: Spatial data structure of Boston GIS datasets*

This general mismatch between the level at which property data is gathered and the building level is common in municipal databases, and problematic in the definition of an UBEM model. Since the entry fields in Table 3-1 are often incomplete, a method had to be implemented so that - depending on the available data - the most accurate individual building descriptions could be deduced. Practically, this required the creation of a SQL database for the management of parcel and tax information, and the association of building footprint geometries in BLD with the appropriate parcel using a spatial join between tables within the GIS tool. Specific data manipulations used are listed in Table 3-2.

*Table 3-2: GIS Data processing steps used to combine entries fields from Table 1 at the building level*

| | |
|---|---|
| 1 | Table data fields from TXP and TXR were joined in a common database table. Based on the established relations between PTYPE and LU codes, queries were developed by code to check for mismatches between the two fields. Wrong associations between property ids were queried and corrected for condominiums. |
| 2 | All property entries were classified in three tables: Individual owner ids, unit owner ids, and main condo ids. Based on this classification all unit type entries were aggregated to the corresponding main condo id (CM_ID). Individual unit info fields (Unit usage, heat/cool system, number of rooms, etc.) were simplified in the aggregated entry to the most common value in the set. Finally, individual owner and condo main entries were combined in a refined table. |
| 3 | Parcel polygons in PRC were joined with the resulting property tax records information using the PID_PARCEL. Parcels with no corresponding record were discarded. Parcels with more specialized property types such as infrastructure buildings, substations, underwater structures, etc. were also eliminated from the data set. |
| 4 | Resulting parcel tax records information were joined to polygons in BLD. In order to link them, a spatial join was created using the centroid of each building polygon as a reference. I.e. all centroids falling into a parcel were assigned the attributes of that parcel's record. Polygons without a viable join were discarded and could not be simulated (See 3.3.1) |
| 5 | Once all polygons in the BLD dataset were connected with an entry of parcel tax records, final queries were processed. All buildings with especial IEL_TYPE codes (Foundation, ruin, etc.) were discarded. Finally those with neither ROOF_ELEVATION data nor NUM_FLOORS data were also excluded from the set. (For discards impact see 3.3.1) |

Massing parameters characterization

As described in Chapter 2, massing 3D models are used in UBEM to calculate areas and orientations. They can be obtained from datasets with varying levels of detail, but in the simplest case, the combination of footprints with roof heights can be used to generate "2.5D" massing models, result of the extrusion of the footprint with a single height. In order to test the feasibility of the simplest viable UBEM, a 2.5D massing was chosen for the Boston model based on the BLD dataset footprints and heights obtained as follows. Up to two height-related entries were available per building, roof elevation (ROOF_ELEV) and maximum number of floors in the parcel (NUM_FLOORS). The building elevation was calculated as the difference between the roof elevation and the average ground elevation of all polygons in a parcel. If both parameters were available, an average floor height was calculated, and verified against an acceptable range between 2.5 and 4.5 m. When the value obtained was not acceptable, the building had to be checked manually against aerial photography, a time consuming step necessary in less than 10% of all buildings. In case either one was missing, the height was estimated based on average floor height for the archetype.

Regarding building footprints, the geometry processing required in their preparation was, the most time consuming step in the massing characterization. Typically, 2D footprint polygons maintained by municipalities are automatically extracted from satellite and flyover imagery, and thus include a large variety of kinks, curves and details (Figure 3-2). Extruding these complex shapes into massing models often leads to unnecessarily detailed models with a large number of surfaces which thermal simulation programs are either unable to resolve or which unduly prolong simulation times. To address this issue, polygon simplification techniques can be applied to GIS datasets which reduce the number of points or segments in the original shape according to rules.

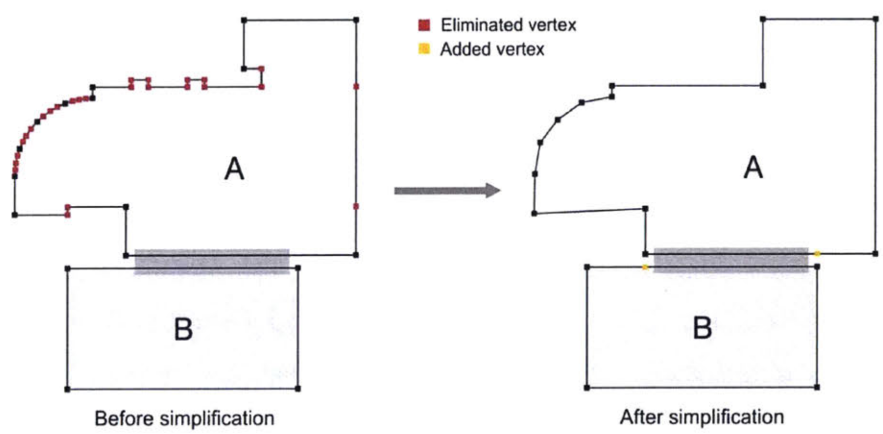


*Figure 3-2: Sample cases of footprint geometry simplification*

However these techniques present two main difficulties for their use in urban modeling: They may (1) change the built area of a building and (2) perturb actual adjacencies between neighboring structures. Additionally, overhangs, cantilevers or canopies might be included in the polygon and might lead to an overestimation of floor area. In this work the standard polygon simplification method available in the GIS ArcMap software was applied [115] to automatically fix adjacencies, following a manual and time-consuming quality control procedure. A similar problem has been addressed in the processing of CityGML 3D models with the CityDoctor tool [116] developed at the University of Stuttgart. Once processed, footprints and heights were combined in the model generation step, as described below in section 3.2. It should be noted that – at the time this study –Boston also had access to a detailed three dimensional model of partial city areas based on LiDAR data. In an effort to limit the amount of data used to that commonly available, the author chose not to use these massings which provided significantly more detail than can directly be handled by simulation programs such as EnergyPlus, but used them as an alternative reference for building heights. As discussed below, going forward, this limitation could be overcome through geometric down-sampling procedures that maintain volumes and adjacencies, a complex computational geometry problem which is being currently explored in research [64].

Characterization and validation of archetype parameters

The generation of archetypes to represent non geometric building properties is always developed in two steps: *Classification* and *Characterization.* During the former, access to measured energy use for every building is useful, allowing classifying them based on empirical data. Unfortunately, despite of various attempts to engage with the local utility, no metered energy use could be made available to the author in Boston. It should be noted that this situation is "typical" since customer privacy concerns frequently prevent utilities from sharing such data, and as of today it should be considered part of the basic datasets available for urban modeling. In absence of metered building energy use, it is generally advantageous for an UBEM modeler to follow existing building type classifications. For the Boston model, the classification step was therefore conducted in collaboration with "Greenwich Energy Solutions", a local building consulting group with previous experience. Working off this precedent, buildings were grouped by two segmentation parameters: Property "Use type" and "Year of construction". The former was used to distinguish between different patterns of occupancy, while the latter served as a proxy to set construction and systems properties. Typical form parameters (e.g. Low rise vs High rise) were ignored since actual building geometry was assigned based on the massing model. Additional parameters in the dataset referring to structure material, roof shape, or type of heating fuel were only available for residential properties and could therefore not be considered.

Regarding year of construction, four periods were considered: Built prior to 1950, 1950 to 1979, 1980 to 1999, and 2000 to present (Table3-3). Although a "year of renovation" field was available, the data was incomplete and its definition was ambiguous, lacking information about the extent of a renovation. As a consequence, only the year of construction was considered during the assignment of archetypes, therefore assuming in the model that none of the buildings underwent any specific energy retrofits since construction. This overly conservative assumption will be revisited below. Regarding use types, the existing 271 codes in the Boston dataset were grouped into 19 usage classes following recommendations from Greenwich Energy and the BPDA (Table 3-4). Since no floor area distributions were available in mixed use buildings, the primary use was applied to the complete structure. The combination of age and usage types resulted in a total of 4 x 19 = 76 archetype definitions.

*Table 3-3: Classification categories by period of construction*

| **Category code** | **Category name** | **BRA categories** |
|---|---|---|
| 1 | Pre1950 | YEAR_BUILT < 1950 |
| 2 | 1950to1980 | 1950 <= YEAR_BUILT < 1980 |
| 3 | 1980to2000 | 1980 <= YEAR_BUILT < 2000 |
| 4 | Post2000 | YEAR_BUILT >= 2000 |

*Table 3-4: Classification categories by use compared to CBECS categories*

| Category code | Category name | RBECS / CBECS category | Simplified code | Simplified name |
|---|---|---|---|---|
| 1 | Residential | Residential | 1 | Residential |
| 2 | Retail | Retail | 2 | Retail |
| 3 | Office | Office | 3 | Office |
| 4 | School/Daycare | Education | 4 | School/Daycare |
| 5 | Medical/Lab/Production | Healthcare | 5 | Medical/Lab/Production |
| 6 | Fire/Police | Public Safety | 6 | Fire/Police |
| 7 | Convention/Assembly | Public Assembly | 7 | Convention/Assembly |
| 8 | Supermarket | Food Sales | 8 | Supermarket |
| 9 | Hotel | Lodging | 9 | Hotel |
| 10 | Restaurant | Food Service | 10 | Restaurant |
| 11 | Athletic Facility | Public Assembly | 7 | Convention/Assembly |
| 12 | Museum | Public Assembly | 7 | Convention/Assembly |
| 13 | Worship | Religious Worship | 13 | Worship |
| 14 | Garage | - | 14 | Garage |
| 15 | Warehouse/Storage | Warehouse and Storage | 15 | Warehouse/Storage |
| 16 | Library | Public Assembly | 7 | Convention/Assembly |
| 17 | College/Academic | Public Assembly | 7 | Convention/Assembly |
| 18 | Transport | Public Assembly | 7 | Convention/Assembly |
| 19 | Industrial | - | 5 | Medical/Lab/Production |

Non-geometric building energy modeling parameters then had to be defined for each archetype including thermal properties of all envelope surfaces and glazing, internal peak loads for equipment and lighting use, HVAC systems settings and usage schedules. All of these parameters were set in consultation with Greenwich Energy Solutions, using as a reference current and past ASHRAE standards and building construction guides for pre energy code periods [45,117,118]. In order to ensure that the resulting simulation results for a given use type were "plausible", they were compared against average metered building energy uses for that usage and climate type from the U.S. Energy Information Agency (EIA) Commercial and Residential Buildings Energy Consumption Surveys (CBECS/RBECS) [90,91]. As part of this process, average Energy Use Intensities (EUI) for lighting, equipment, hot water, heating and cooling were extracted from the EIA surveys and used to estimate average annual values through iterative simulations of an average sized building from each use type. In cases in which the Boston use type could not be matched to any of the building types in the EIA surveys, it was merged with the closest category for which survey data was available, reducing the final archetype count from 76 to 52 (Table 3-4). As an example, museums and libraries (Codes 12/16) were grouped under Convention (Code 7).

Archetype characterization is without doubt the step municipalities are least prepared to develop in UBEM, since none of the required information about the building or its occupants is recorded in any way at the urban level. In the US, the only sources available are the so called reference energy-modeling buildings developed by ASHRAE and the US Department of energy [119,120], which provide typical archetype inputs by main use types and periods of construction nationally. In addition to their lack of regional specificity, they do not cover all possible uses, vintages, and construction styles of buildings. Furthermore, they do not use standardized classification categories, requiring the intervention of modeling experts to assign them to the specific building types of a particular municipality. Once a set of archetypes is available, all model parameters required for a thermal model can be stored in an archetype "template", a file format which can be interpreted by the modeling software is use and assigned to each building accordingly. This could potentially be achieved by expanding established Building Information Modeling (BIM) formats such as gbXML (gbXML, URL: http://www.gbxml.org), or by adapting a GIS database format. However, these approaches present limitations for their implementation in a large number of multi-zone models. To streamline archetype assignment, the author implemented a new library file format for archetype "templates", used to store the final 52 archetypes as described in the following section.

### *3.2.2 New text file format for archetype templates*

The task of gathering information for model inputs and entering them in simulation software constitutes the first step in any energy modeling workflow, both for single buildings in a BEM or for a variety of archetypes in UBEM. The process can be very time consuming, and requires adequate knowledge of building physics to avoid errors. In a survey developed by the author of 180 professional BEM modelers, 38% of participants responded that they spent between 20-50% of their modeling time gathering data inputs and entering them in their models [51]. More interestingly, 87% indicated a willingness to use pre-made data inputs if provided in a standard format and validated by professional or academic institutions. This external provision scenario could be particularly effective in the case of UBEM archetypes, but current file formats for model inputs do not allow its implementation.

In the case of BEM software, data libraries typically help with input management by allowing the user to store and classify personalized materials, schedules and systems. In addition, a few tools such as DesignBuilder [49] include pre-populated libraries of these components, very useful for early design modeling. However none of them are offered in an open and standardized file format, making their exchange between modelers and collaborators very difficult. There have successful contributions of standard formats focused on specific model inputs [121,122], or full models of specific buildings including their specific geometry like gbXML. None of them however, packages all non-geometric inputs as a geometry agnostic template, which could be very useful in early design modeling.

The lack of a standardized file format to store all model inputs is especially relevant for UBEM, because archetype have to be assigned in an automated way to hundreds or thousands of buildings. Using database tables in GIS for this purpose is a limited solution, since the data hierarchy within an energy model (e.g. a material, within a wall, within a building) cannot be easily represented. More importantly, there is no established data format for an institution or a municipality to produce, maintain and distribute validated archetype datasets, streamlining UBEM implementation and use. To address these limitations, for the purposes of both early building design and urban energy modeling, the author developed a new Template Library File (TLF) format as part of this dissertation [51]. The term "template" refers to a comprehensive set of energy simulation inputs that characterize all attributes of one or multiple thermal zones, and which can be combined with 3D geometry data in order to generate a full energy model. In addition to the TLF format, an editing tool for template libraries was introduced in this work as well.

The purpose of the TLF is to combine in a single standard file a collection of templates, to be assigned to specific buildings in a model, urban or otherwise. In the TLF, for a particular template's entry, all building model parameters are grouped into three main categories: (1) Constructions, (2) Thermal Loads and (3) Conditioning systems. Within these categories, each model parameter (e.g. "Façade wall" in constructions, or "Occupancy" in thermal loads) is assigned a specific value, which can be a number, a Boolean operator, or the name of another data object (e.g. "Insulated masonry 3" for "Façade wall", or "0.02 pp/m2" for "Occupancy). The resulting data structure is a three level tree: Template, category, and parameter. In order to store building template definitions, the file is organized into two main sections (Figure 3-3): *Section A* includes a list of template definitions, each one representative of a different archetype. *Section B* contains definitions for all their data dependencies. These include opaque and glazing constructions (assemblies of materials), opaque and glazing materials, plus yearly, weekly and daily operation schedules. As a proof of concept, the Template Library File (TLF) has been implemented as both an Extensible Markup Language (XML) file and a JavaScript Object Notation (JSON) file.

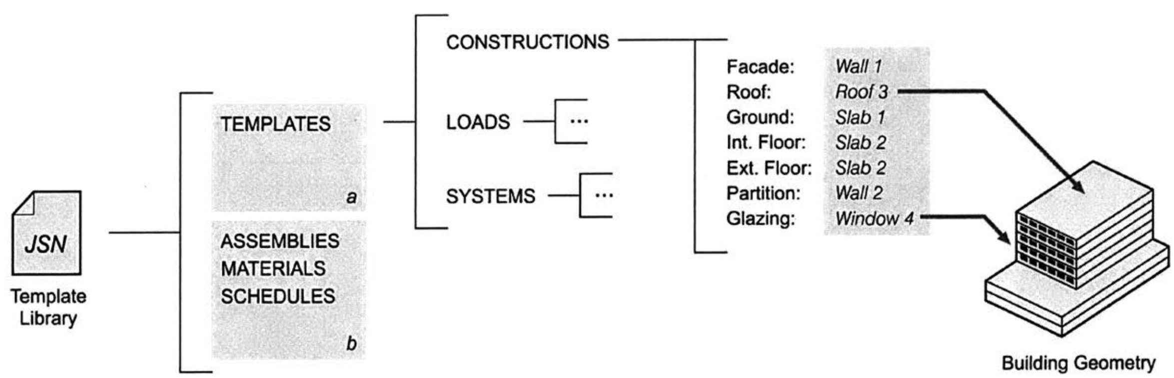


*Figure 3-3: Template Library File structure diagram*

These existing file types were chosen because they offer a flexible classification of data, can be read by humans, and are highly compatible with web applications. The use of XML in building simulation for the definition of model parameters is not new, with gbXML being the current standard for BIM files. Similarly JSON files are currently used for the storage of geospatial data for online applications. The main innovative attribute of a standardized TLF is that it allows separating the production of archetype templates from the energy modeling effort itself. Hence, in the implementation of an UBEM model, a building expert or a professional institution (e.g. ASHRAE, USGBC) could be responsible for providing validated templates, while the definition of analysis scenarios and the simulation are run by an urban official or planner. This shared workflow would streamline model setup, improve overall model quality, and liberate urban modelers from the specialized time consuming task of defining archetypes. A framework for the application of such workflow is discussed further in Chapter 7.

Since in the envisioned workflow the task of the management of template files is separated from the modeling itself, it is necessary to provide a digital infrastructure for their manipulation. The authors propose that the typical library functionality present in BEM software could be isolated as an individual tool independent of any simulation engine in particular. As part of this work a simple template editor tool was developed as a stand-alone application programmed in C#. The template editor consists of a simple explorer interface divided in two panels (Figure 3-4). On the left panel a data tree representing the open template library provides access and control of all stored components. On the right panel selected component attributes can be reviewed and edited. Initial versions of the editor have been successfully implemented as a plug-in application for two simulation tools currently available for Rhinoceros/Grasshopper: Archsim, a BEM interface for EnergyPlus used in this study [52] and UMI, the urban modeling design suite developed by the MIT Sustainable Design Lab [108].

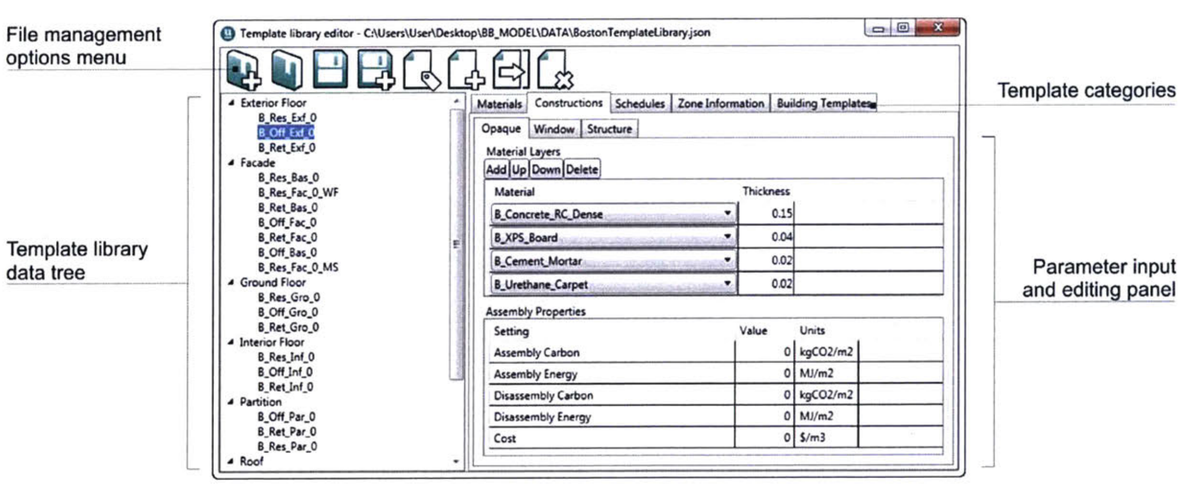


*Figure 3-4: Template Library File editor tool screenshot*

*3.2.3 A Toolset for UBEM generation*

Once data inputs for the climate, massing, and archetypes are available, thermal models have to be generated for each building to be simulated in a particular engine. As explained in the introduction, the objective in Boston was to test the feasibility of the simplest viable UBEM model, still distinct in its capabilities from traditional bottom up engineering models. In that context, the author chose to define that minimum viable UBEM as one that: Uses dynamic thermal simulation, takes into account building context, and implements multi-zone models, but only considering one zone per floor. A few software tools have been developed so far in research for this purpose, which were discussed in Chapter 2. However, none were capable to integrate raw GIS datasets with archetype information at the time this study was developed. For that reason, a custom modeling toolset was developed as part of this dissertation to produce, in an automated way, individual models compatible with EnergyPlus [16]. The steps required included creating 3D massings, dividing them into thermal zones, solving adjacencies between neighboring buildings, and assigning an archetype template to each zone (Figure 3-5).

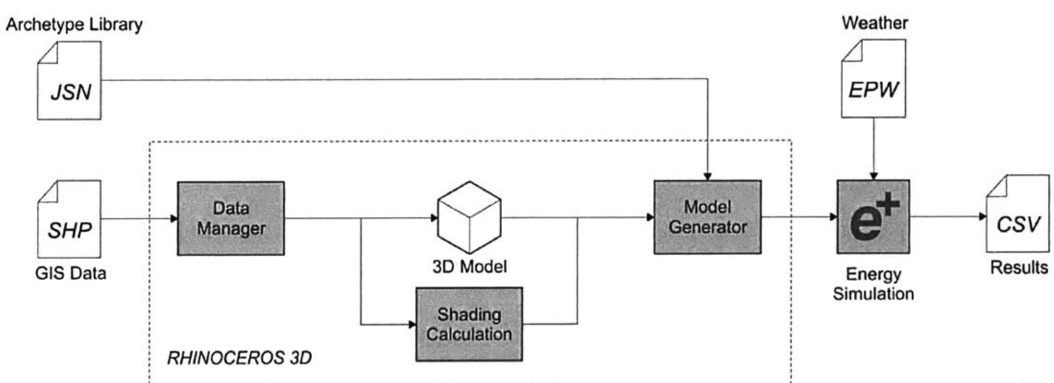


*Figure 3-5: Replicable UBEM modelling workflow*

The toolset was implemented as a plug-in for Archsim [52], an already existing interface for EnergyPlus, part of the In the generation of the Rhinoceros 3D CAD environment [123], ubiquitous in architecture and design, and selected for its open programming interface. In order to produce the 3D massing, simplified footprints were imported from GIS shapefiles into the Rhino3D through the new toolset. These were then extruded to the processed building height, using custom C# application components within Rhino's parametric plugin Grasshopper [123] resulting in the full massing. The rest of the thermal model generation, as shown in Figure 3-6, was developed as well through custom made components which further processed the 3D massing. Buildings were divided into the determined number of floors, and adjacencies with surrounding volumes were fixed using the tool capabilities.

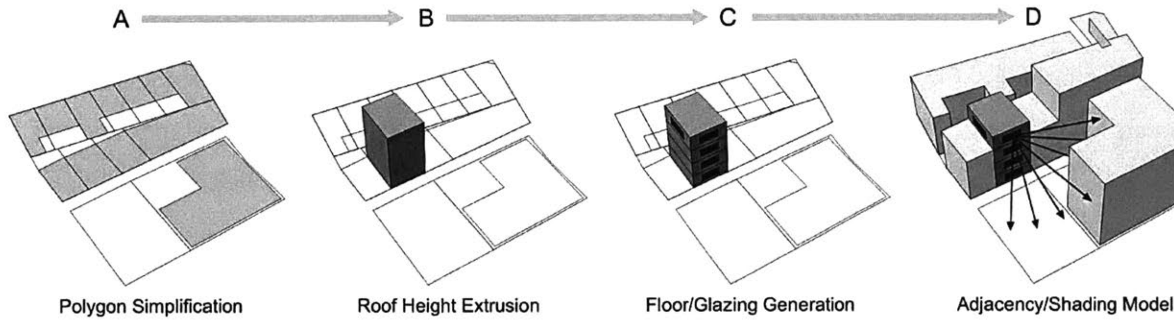


*Figure 3-6: Building geometry modeling process*

Next, one window was added on each free facade wall according to the building's Window to Wall Ratio (WWR). Although some methods have been proposed for the automated estimation of window areas from aerial imagery [72], in current available urban datasets WWRs are not available. In the Boston model WWR was included as a fixed archetype parameter, defined per use type according to the city consultant's input. To characterize the specific local shading conditions for each generated window, potential shading surfaces were identified in the 3D model based on a search radius of 300 m. Based on those, a raytracing algorithm was used to select those affecting the solar radiation on the window and include them in the model. In a last processing step within Rhino, simulation parameters from the JSN building template library were assigned to each thermal zone. As described before, in the Boston model, the authors decided to create only one thermal zone per floor of the building in order to maintain manageable simulation times for the whole city while still capturing variations in energy use due different solar exposures. A more detailed zoning scheme, such as the core and perimeter method proposed in ASHRAE 90.1 Annex G [45], would have exponentially increased the number of zones and simulation times. It should be noted that the more advanced "shoeboxer" method referred in Chapter 2, have been recently developed to address this limitation [22]. While it would have been the preferred simulation route for the author, its implementation as a tool was not finished at the time of this study.

Finally, in the chosen dynamic energy simulation engine (EnergyPlus) each building energy model was stored in an IDF text file, packaged and ready-to-run. Once all modeling steps were completed, IDF files for all parcels in the model were generated using the capabilities within Archsim. Given the limitation of the number of surfaces that Rhinoceros 3D can process in a single model, the Boston dataset was divided into 14 neighborhoods during model generation, and EnergyPlus files for each building were temporarily stored for further processing. The modelling workflow described so far was built independently so that any city with equivalent GIS datasets could reuse it.

### *3.2.4 Model Simulation and Processing*

In the case of a large UBEM, executing multi-zone thermal simulation files for tens of thousands of buildings and handling the resulting massive amount of data pose a logistical challenge. In this case a parallel computing approach was chosen for the Boston project and individual IDF simulations were distributed and run on two 16 core desktop computers, resulting in a net simulation time of approximately 60 hours over one week for the complete Boston. This time does not include all previous model building steps, which amounted to a large number of hours as reported in the following results section. The resulting hourly and yearly results were processed and compared against national use type EUI averages (as described in section 3.3) and total fuel consumption values for 36 zip codes in Boston (electricity and gas) provided by the BPDA for 2014. Missing and unidentified values reduced the dataset to 27 useful zip codes which were eventually used in the results analysis.

## 3.3 Results

The steps covered in section 3.2, produced a viable citywide UBEM for Boston. The following sections present the results of the generation and simulation workflow, focusing on the processing of the available datasets, the general accuracy of the model, and the type of demand values available in the end.

### *3.3.1 UBEM data processing*

Following the data manipulation procedures laid out in section 3.1, a portion of the initially available records for taxes (TXR), parcels (PRC) and building footprints (BLD) had to be discarded due to missing or inconsistent data entries: During the initial step, 163,499 tax records were aggregated into 99,803 parcel records. After joining the parcel records with parcel geometry (PRC), 581 records did not produce a match. Another 5,805 parcels were found to have a property type not fit for being modelled such as underwater structures, storage silos or substations resulting in a further sample reduction of 6.4%.

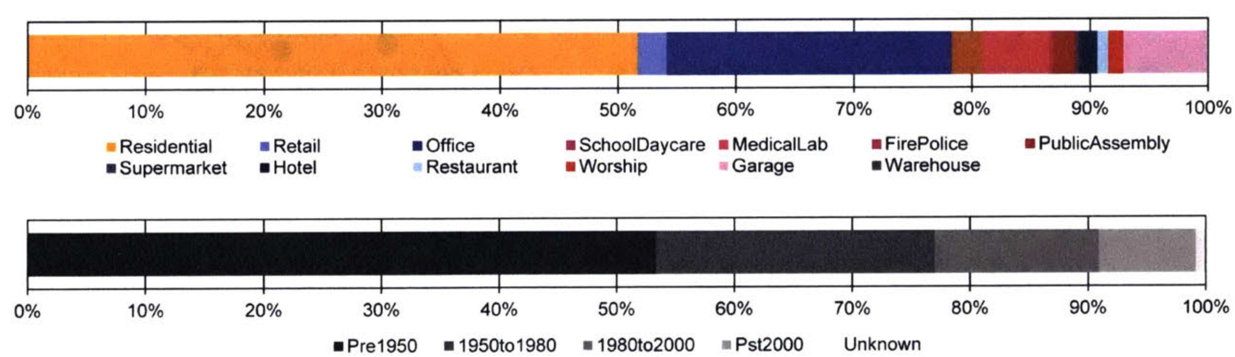


*Figure 3-7: Segmentation of Boston building floor areas by archetype use and age*

The BLD footprint dataset originally included a total of 128,593 polygons. From that set, 552 polygons representing buildings under construction, in ruin or mobile structures were eliminated along with another 25,602 outside structures, such as garden sheds, kiosks, etc., leaving 102,439 polygons. These remaining polygons represent 98% of Boston's built floor area. During the ensuing data manipulation steps, more structures had to be discarded because joining BLD footprints with their pertaining parcels resulted in a mismatch (549), building heights were faulty (386) or polygons represented very small building features (5,302). As a whole, only 3% of the building floor area could not be modelled due to data issues. Within the remaining dataset, 3,439 building footprints were defined as "Tax Exempt" in the Boston property type database and could therefore not be assigned to any of the archetypes. Similarly, 1,561 footprints did not have a year of construction, so generic "after 1950" conditions were used. Results show residential and office are the two main types, with floor areas of 52% and 24% respectively (Figure 3-7). The distribution of archetype uses and ages however is not uniformly distributed throughout Boston (Figure 3-8), and that affects the accuracy of the model discussed in the next section. The analysis shows how commercial buildings are, as expected, mainly concentrated in downtown and surrounding zip codes, and how those are interestingly also the areas with more recent structures, while in residential suburbs a majority of building were built before the 1950s. The ratio of buildings which cannot be modeled or classified depends solely on the data quality of available datasets, and hence it is in the power of municipalities to improve these results.

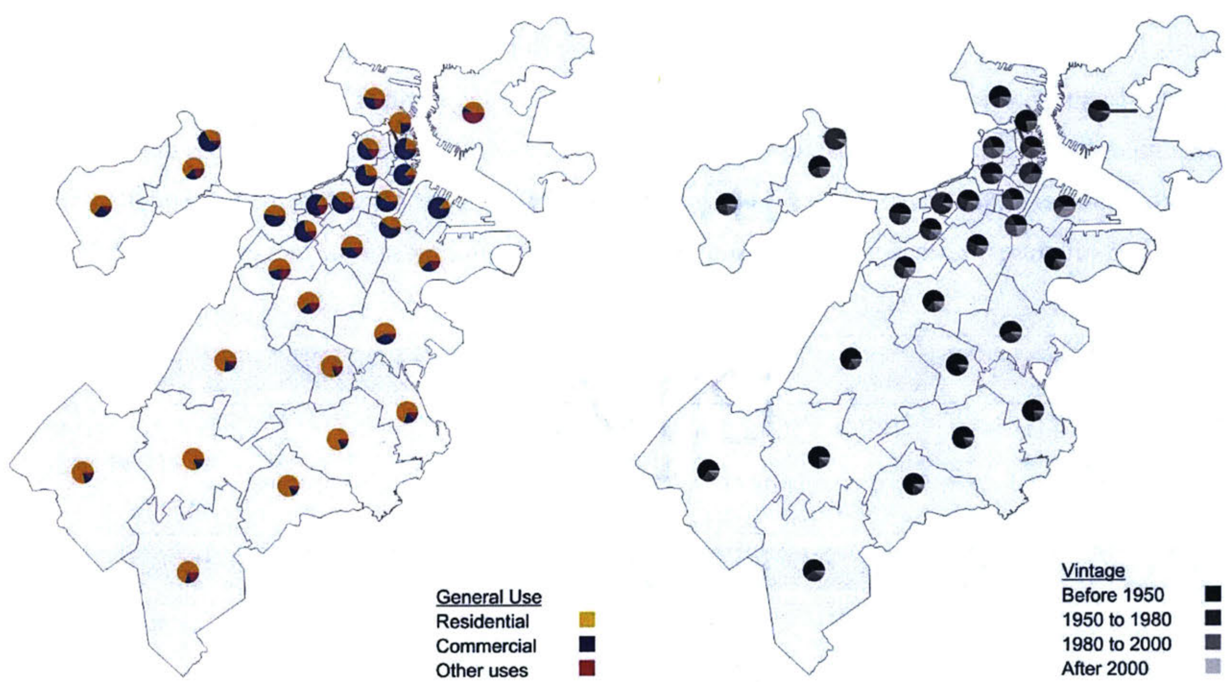


*Figure 3-8: Use and age floor area distribution in Boston by Zip Code*

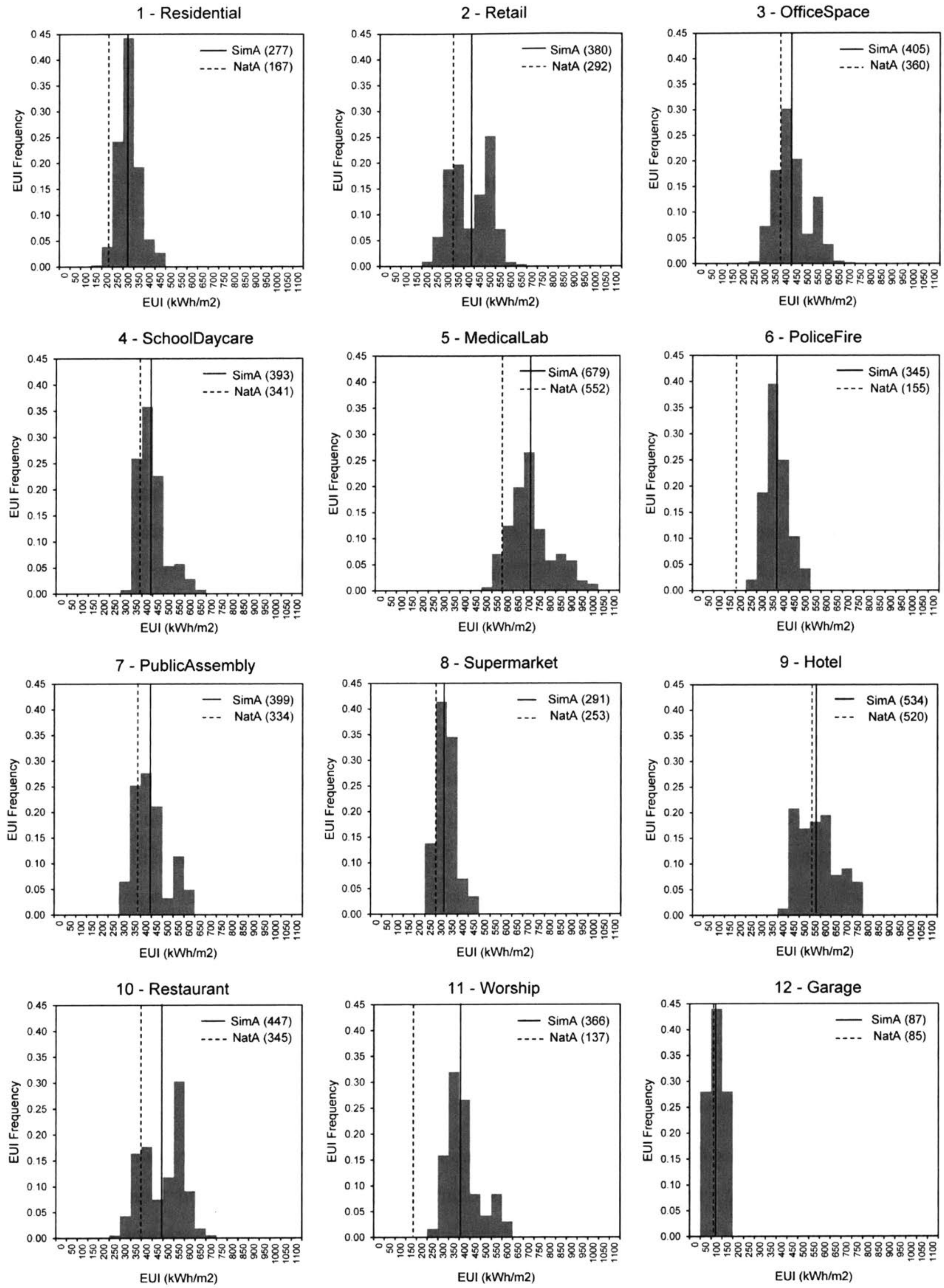


*Figure 3-9: EUI distributions with simulated (SimA) and CBECS (NatA) averages for 12 use types*

*3.3.2 Results comparison to CBECS/RBECS and zip code total energy use*

Following the thermal model generation workflow proposed, annual hourly simulation results were aggregated by parcel ID into "electric loads" for space cooling, plug loads and lighting loads as well as "heating loads" for space heating and domestic how water. Figure 3-9 shows the resulting EUI distributions and simulated averages (SimA) sorted by building type, and compares them to the CBECS/RBECS national averages (NatA). Average EUIs ranged from a minimum 87 kWh/m2 for garages to a maximum of 679 kWh/m2 in the case of medical and lab buildings. The error of the average modeled EUI compared to the CBECS/RBECS averages ranged between 5% and 20% for most types with the simulated value always being higher than the CBECS reference. This finding is not surprising given that those averages were also used in section 3.2 to calibrate a single, unshaded "default" building of the same archetype. The variation in Figure 3-9 distributions hence illustrates the effect of building form and context shading on energy use, as the amount of solar radiation received varies. A known model limitation is that a single programmatic use was assumed for all buildings even though mixed-use scenarios are common in Boston. In the case of Fire/Police and Worship facilities discrepancies between UBEM predictions and CBECS/RBECS are 122% and 167% respectively, and may have been caused by their non-regular spatial distribution, difficult to represent in the simplified zoning scheme used.

In addition to a general comparison with national average EUIs, the yearly model results were compared at the aggregate level to total gas and electricity use by zip code, provided by the BPDA for the city of Boston in 2014. An average absolute error of 40% in the total energy use (both gas and electricity) was found for 23 zip codes, with individual absolute errors ranging between 5% and 94%. When electricity and gas were individually analyzed, average errors of 67% and 71% were observed. Gas related errors proved to be larger in those zip codes with a bigger ratio of commercial to residential building uses, while the inverse happened on highly residential zip codes. The model assumption that all commercial buildings were using gas for space heating (made in the absence of data on the subject in the city database) might have been responsible for such relationship. However, the zip code electricity and gas total provided by the city did not document the number of parcels included or the exact boundaries, making it impossible to match results accurately in the comparison.

*3.3.3 Spatial and hourly load profiles*

The simulation results for Boston, produced as described in previous sections, provided the planning department with building energy demand datasets characterized both spatially and temporally. These allowed the exploration of energy use in a level of detail not possible before, and to produce energy maps which could be used as a framework for energy supply scenario analysis later on.

In order to understand the geographic location of main electricity and gas consumers, annual demand maps were produced for each zip code and district in the city. Since commercial buildings were assumed to use gas for space heating, gas demand characterizations need further confirmation by the city of Boston before use. These maps not only can be used to target specific building clusters as part of the Boston climate action plan, but also serve a baseline model for comparing with disclosed energy consumption. As an example of the type of maps which can be generated using the UBEM, Figure 3-10 shows the annual Energy Use Intensity (EUI) by building in the neighborhoods of Back Bay, South End and Columbus, ranging from a minimum 87 kWh/m2 in car parks, to well over 500 kWh/m2 in commercial buildings.

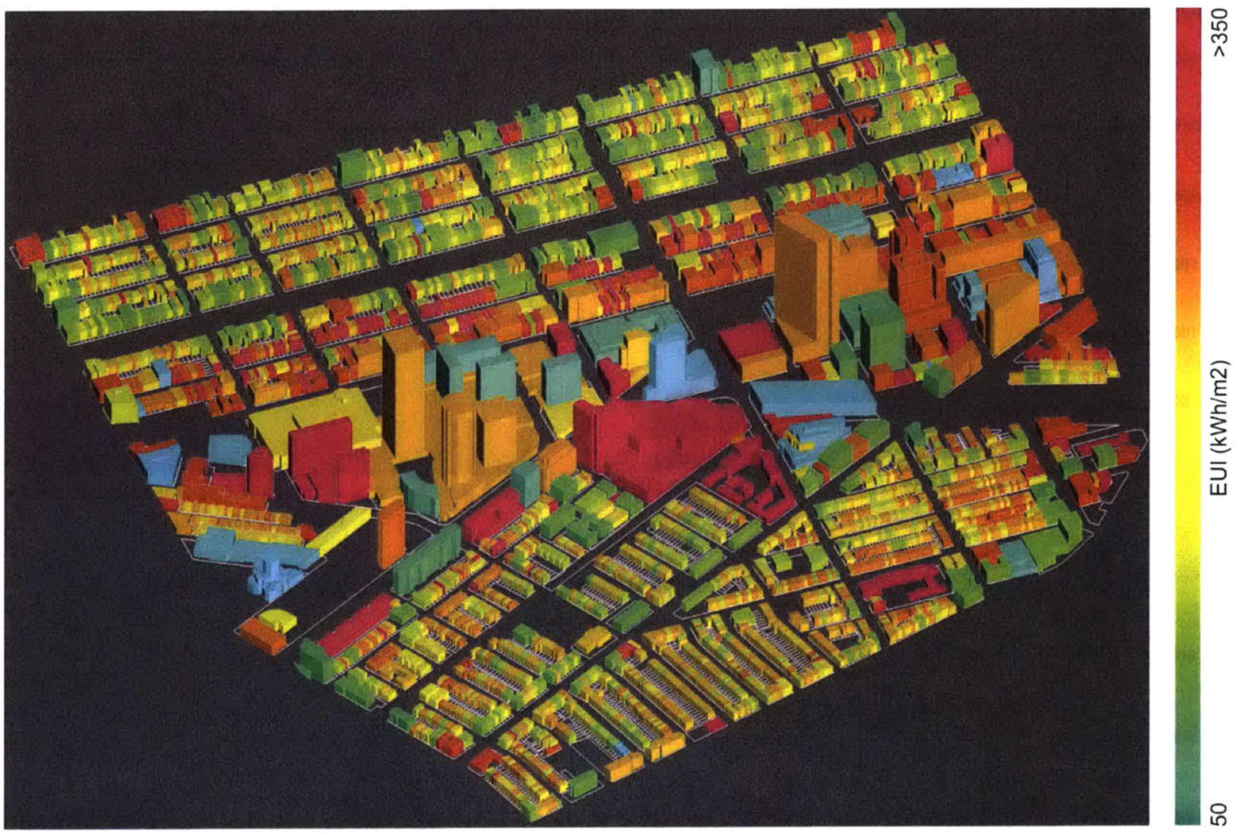


*Figure 3-10: Simulated building EUIs for Back Bay, South End and Columbus neighborhoods*

Figures 3-11 and 3-12 show predicted hourly use by building type and fuel for the hottest (July 7th) and coldest (January 30th) days in the year in Boston. The summer load profiles suggest two peaks during the morning (2,221 MWh) and the late afternoon (3,173 MWh). Figure 3-11 shows that the latter peak is mainly caused by the concentration of cooling loads for both residential and non-residential buildings as some residents return home from work or school while others stay longer. The figure reveals that the majority of loads on a summer day are electric whereas heating fuel is mainly required for hot water use. Throughout most of working hours commercial buildings are responsible for over half of the load. Only in the late afternoon residential cooling accounts temporarily for about a third of the load.

During winter energy loads are higher at night, with a significant peak in the early morning (6,217 MWh) caused by an increase in heating needs when night setback temperatures are reversed to daytime set points. This peak is most likely exaggerated as the model assumes all residential buildings change from nighttime setback to daytime set point temperatures between 6 AM and 7 AM. This concurrency of loads is a fundamental problem in a basic UBEM resulting of minimum urban datasets, since in the absence of occupant stochastic models all internal thermal loads within an archetype happen exactly at the same time, overestimating peak loads even at the aggregate level.

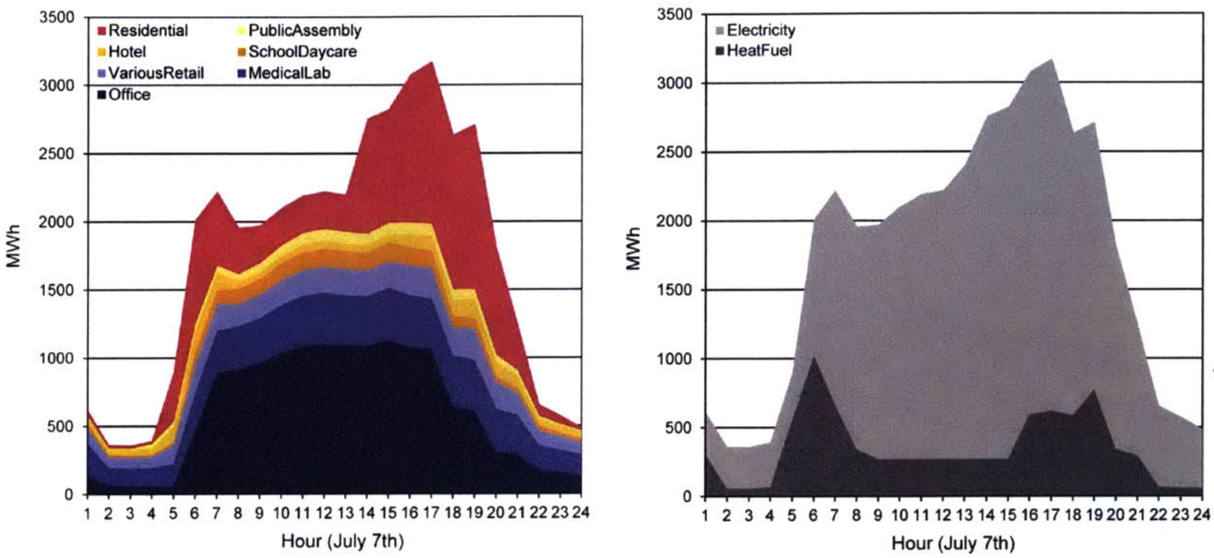


*Figure 3-11: Simulated Boston hourly energy demand by (a) use group and (b) fuel type for summer peak day*

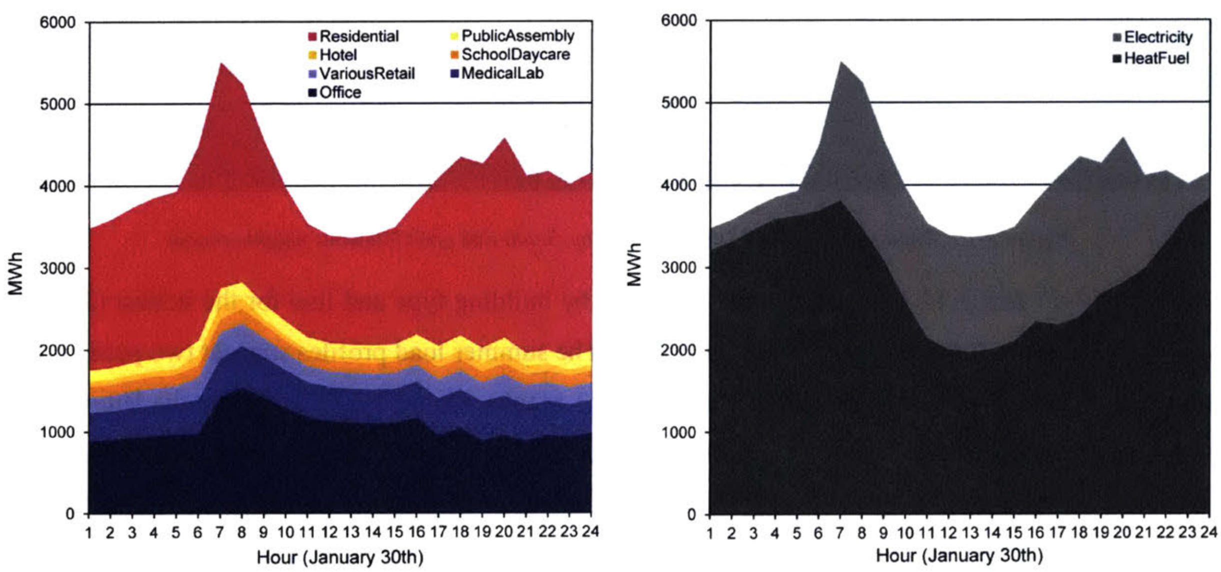


*Figure 3-12: Simulated hourly energy demand by (a) use group and (b) fuel type for peak winter day*

### 3.3.5 *Effort level and data limitations*

Although previous sections have demonstrated the feasibility of citywide UBEMs when using currently available datasets and computational tools, they have also highlighted the large number of processing steps involved in their generation. In order to allow for the large scale implementation of UBEM, it is necessary to understand and document the level of effort required, as well as the main modeling barriers responsible for it. In terms of expertise, it required knowledge in GIS database management, application programming, and building science, some of which are mot typically found within a municipal department. In this particular case a majority of the work was developed by the author, with the collaboration of an outside energy consultant hired by the city for the characterization of archetypes, and of a master student in urban planning which shared a fraction of the data processing work in the later stages of the model. While the case study was developed as part of a long term project in collaboration with the BPDA, the modeling workflow presented in this dissertation was developed over a total of 6 months, in which the author was not exclusively dedicated to the project. Specific tasks were developed in shorter periods of time along the semester, accounted for in Table 3-5 assuming 6 hours of work per day, to a total of 50 - 90 days. In addition to the simulation time itself, which was determined by computational power and the thermal modeling technique, the most time consuming efforts were concentrated in the *Characterization* phase, and mostly due to data-related barriers and limitations. The three most relevant tasks in terms of effort level and potential for improvement are: (1) Processing and mapping datasets with a unique building ID, (2) Simplification of building geometry, and (3) Characterization of archetypes.

*Table 3-5: Approximate gross time dedicated to each UBEM modeling phase*

| Workflow Phase | Modeling Task | Approx. Gross Time |
|---|---|---|
| Characterization | Gathering GIS and tax assessment datasets from the city | 2 – 3 days |
| | Mapping all data to a single building ID in a common database | 7 – 10 days |
| | Simplifying and cleaning building geometries and heights | 7 – 10 days |
| | Classifying building into archetypes by use and age | 2 – 3 days |
| | Manually revising undefined or incomplete data entries | 7 – 10 days |
| | Characterizing and validating archetype parameters | 20 – 30 days |
| Generation | Creating 3D models in Rhino3d for buildings and shading | 3 – 4 days |
| | Creating EnergyPlus files for each building | 2 – 3 days |
| Simulation | Running EnergyPlus simulations | 7 – 10 days |
| | Processing and analyzing result files | 3 – 4 days |

In the first case, the large time required for unifying datasets under a single ID was the result of the lack of consistency in the spatial data resolution used in each case. While building heights were given by footprint, number of stories and age were given by parcel, and building use was defined by property owner. As presented in the methodology this step became particularly problematic for parcels including condominiums or multiple owners. Regarding geometry simplification, most time was spent checking problematic buildings with complex floorplans and mixed heights against aerial photography, to guarantee their simulations would not fail. Finally, the largest effort in terms of time was the characterization of all simulation parameters for each archetype considered in the model, which had to heavily rely on national reference buildings, since no detailed building information has been gathered for that purpose in the city. Table 3-6 below summarizes the main identified data shortcomings for UBEM.

*Table 3-6: Main data limitations and barriers for UBEM modeling*

| **Data limitation** | **Description** |
|---|---|
| Spatial resolution | Most digitally available information exists only at the scale of the parcel but is not defined by building. This is result of most of such data being part of property tax assessments, where information is gathered by owner ID. At the same time no unique building ID exist, making it impossible to link each parcel with the structures it contains and each data point with the right structure and floor. |
| Limited tax data | Property tax assessments represent almost the only building information source ubiquitously available in US cities, but miss many fundamental basic inputs necessary for archetype classification. Particularly important is the lack of WWRs, glazing type, insulation levels and number of occupants. In addition, fundamental fields such as dates of construction and renovation are often incomplete. |
| Single vs mixed use | Property types, main identifier for the activities within a building, are defined by tax assessment parcel only. In the case of mixed use parcels or buildings, labelled as such in the tax database, it is impossible to know which buildings or floors correspond with which use. |
| Complex footprints | Typical building footprints available in GIS datasets for US cities have a high level of polygon detail, unnecessary and sometimes problematic for the generation of thermal zones. Available simplification processes, are not designed for energy modeling, and can result on excessive changes in the shape of the building, missing adjacencies with neighboring structures, or modified areas. |
| Roof structures | Simplified 3D building models are not available in most cities, requiring modelers to assume flat roofs for in all cases, and ignore the effects in energy use of sloped roofs and attic spaces. |
| Constructions data | The lack of local databases of construction solutions and HVAC systems by building, force modelers to use generic building definitions in the characterization of building archetypes. |
| Metered energy data | Metered energy demands are rarely available at the building scale in large enough samples, due to privacy and legal concerns. As a result, archetype classification parameters, and general characteristics cannot be validated in the generation of the model. |

## 3.4 Discussion

In the light of the above presented results, this section discusses the feasibility and scalability of the Boston UBEM approach, as well as whether model results justify the overall effort level.

### *3.4.1 Model feasibility and energy data*

The previous methodology and results have confirmed the research hypothesis that it is in fact possible to generate and simulate a viable citywide UBEM, using only those urban datasets currently available and maintained in typical US municipalities. The example of Boston has shown that a reproducible modeling workflow can be implemented, which automates the big majority of processes in the production of a city wide model. Weather data can be obtained from local stations, and building 3D massings can be produced from basic GIS shapefiles. Some remaining modeling challenges include situations in which urban microclimatic conditions need to be modeled in detail or specific cases in which complex building geometries cannot be represented by extruded volumes, but the available data is sufficient for a majority of scenarios. However, the experiment has also highlighted that available building information remains limited and classification of buildings into archetypes.

Populating a quality library of archetype templates is time consuming and requires local building expertise, as well as access to detailed audits and/or metered energy use. In most cases it is therefore unlikely that a municipality has the expertise or budget to independently develop it. In Boston, only a very generic characterization of building types was possible as it relied mostly on preexisting reference buildings developed at the national scale, hence missing any particularities of local constructions or occupant types. In the authors' opinion, it is rather incumbent on municipal, regional, and national organizations such as the US Department of Energy, or the US Energy Information Agency to commission the development of such archetype libraries for a particular building stock and to orchestrate their maintenance and distribution. The proposed open and publicly available template library file format may further speed up the adoption of the data by UBEM modelers.

A particularly important step in the characterization of such building archetypes is occupant behavior, as extensively recognized within the field of building simulation. Statistical methods based on metered energy use data could better characterize occupant-related parameters in archetypes if the data is accessible in large enough samples (both temporally and spatially). Chapters 4 and 5 of this dissertation propose an implement an archetype calibration approach for that purpose. Such techniques however typically require the cooperation and dedication of resources by local utilities, and raise important issues of data accessibility and privacy which need to be addressed for UBEM to become and effective urban policy tool. Alternatively, municipal initiatives such as energy reporting and disclosure programs (BERDO in Boston) will likely provide an effective source of data going forward [124]. A framework in which metered energy data for specific buildings can be exchanged between utilities, cities and modelers is, in the opinion of the author, a necessary component for the widespread adoption of UBEM.

A key lesson regarding the relationship between accuracy and metered data is that the diversity of EUIs in the city can only be modelled confidently at the temporal scale for which the real data is available for comparison. As reported in the methodology, no individual building metered data was provided in Boston, and only an average annual EUI comparison was possible against national averages. The comparison suggests that building uses with singular spatial characteristics, such as theatres, churches or fire stations cannot be represented reliably in the resulting generic UBEM. In this context, the author notes that while the greatest effort in Boston was placed on defining realistic hourly usage profiles that led to peak loads shown in Figures 3-11 and 3-12, and while these curves are qualitatively consistent with measured building stock load curves reported elsewhere [125], it was impossible to guarantee an accurate representation of such profiles in the absence of hourly data.

### *3.4.2 Barriers for implementation*

Section 3.3.5 of this chapter identified the most time consuming phases in the generation of Boston's UBEM, and some of the key barriers responsible for them. For the large scale application of UBEM methods, these barriers need to be addressed so that the potential applications of the model can justify the effort level necessary in its preparation. As described in the results, the main limitations are concentrated in the Characterization phases of the workflow, where available data is translated into a set of parameters useful for UBEM. Since building related urban GIS datasets do not use a standardized set of data fields across cities, the cumbersome process has to be repeated in every municipality. However, based on these results it is possible to identify multiple opportunities for streamlining and automation. The author envisions a workflow possible today, in which initial focused meetings between modelers and municipal department are combined with automated checking routines to detect and account for missing or faulty data. Such workflow would be a onetime effort, setting the foundation for a live model to be maintained by the city, and it would require the improvements to existing data practices described below.

<u>Unprocessed geometric data:</u> Regarding the required 3D massing geometry, the Boston study showed that although models based either on extruded footprints (as used in this study) or LiDAR data are readily available in a majority of cities based on existing datasets, the level of detail resulting of their generation is typically inadequate for the purpose of energy modelling. Currently a significant amount of manual work is required to guarantee that unnecessary polygon details are eliminated to reduce simulation times, and that correct adjacency conditions and building floor areas are maintained while doing so. Better polygon simplification algorithms are required, which can automatically perform these geometric operations. Equally, automated image analysis is required for gathering of WWRs by façade, to allow for a higher accuracy in the representation of building glazing. A fair amount of research is focused on these limitations and it is likely that they will be solved and fully automated in the near future.

Non-unified data IDs: The effort of assigning parameters from multiple datasets to each individual structure showed that in current urban datasets no single standardized ID number is given to buildings and instead available information is stored at the scale of parcels or tax properties. This practice does not allow for storing specific information about multiple buildings in one parcel or belonging to the same owner. Furthermore, the ID fields currently in use are typically not consistent within the existing datasets. Cities should start referencing spatial units with individual IDs that go beyond parcels and include buildings and floors. Overcoming this limitation becomes especially important for modelling dense urban areas where single structures accommodate multiple usage types by floor, a level of detail necessary for effective UBEM and still missing. The use of self-contained units (SCU) as a spatial energy related analysis unit which might represent a section of a building with a common use type regardless of ownership has been proposed as a potential framework to better characterize mixed use areas [82].

Lack of digital building data: Equally important for effective UBEM applications is the detailed documentation of building construction and operation information. In this study, all archetype parameters had to be defined based on reference buildings, with no basis on empirically collected information from buildings in Boston. Ironically, a wealth of such data is currently collected during building permits, audits or property sales, but it is not digitally captured or linked to citywide databases. These instances constitute an opportunity for cities to systematically collect constructions, systems and renovations data, which could significantly enrich the limited information available in tax assessment datasets. However, to take advantage of it, municipalities need to modernize their data practices by implementing a digital and centralized reporting process, in a similar fashion to Energy Performance Certificates as currently required within the European Union [94]. The proposed template library file could be also applied in this documentation process, and updated with the dates and characteristics of renovations and use changes.

As far as scalability is concerned, it seems that all of the above hurdles can be addressed in the short to medium term and that UBEMs have a large potential to play a role in urban planning. A remaining and fundamental question however is whether the information provided by these models justifies the required modeling effort for the interested urban stakeholders, which will be discussed in more detail in Chapter 7.

## 3.5 Summary

The previous sections presented an automated UBEM modeling workflow and applied it to generate a citywide model of Boston. Key contributions of the study are:

- It is feasible to generate a citywide UBEM based on currently available and maintained municipal datasets, capable of producing spatially and temporally detailed energy demand data.
- In the absence of individual building metered energy data, the resulting UBEM can only be expected to estimate mean annual EUIs by archetype within a 15-20% error range when compared to the national average EUI for that building type.
- While feasible, the generation of a citywide UBEM is a very time consuming effort, mostly concentrated on the combination of disparate available datasets, and the characterization of building archetype templates.
- Key modeling barriers for large scale implementation of UBEM include the current complexity in unprocessed geometric data, the need for a unified data ID at the scale of buildings, and the lack of locally collected building and occupant data.

Chapter 4

# Bayesian approach for UBEM archetype calibration

While the previous chapter has shown that it is possible to generate and run a citywide UBEM based on commonly available urban datasets, it also highlighted a need to verify how accurate those models are vis-à-vis measured building energy use. For an UBEM to become an effective tool in the evaluation of future urban energy scenarios, the model has to accurately represent current overall amount and diversity in energy use between different buildings. Based on a case study of a residential district in Kuwait city, this chapter proposes a Bayesian calibration method for the characterization of archetype parameters using a limited training sample of metered energy data, and compares its performance with that of uncalibrated archetypes. Section 1 reviews previous uses of uncertainty analysis in individual and urban building energy modeling. In section 2, Bayesian calibration and comparison modelling techniques are presented in detail, followed by a description of the Kuwaiti case study. Later, a validation experiment is presented in which the parameters calibrated with the training dataset are applied to a second sample of buildings belonging to the same archetype. Results are presented and discussed in sections 3 and 4.

*Elements of this chapter have been published in the Energy and Buildings Journal:*

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## 4.1 Introduction

In order to be effective for any future scenario analysis, an UBEM has to be able to reproduce current energy demands with sufficient accuracy. The grouping of multiple buildings into equivalent archetypes may introduce significant errors in simulation results, which have so far not been systematically quantified. As described in Chapter 2, if archetypes are characterized deterministically, they are prone to underestimate the real diversity of demands. On the other hand, the lack of constructions, systems and occupant empirical data for individual buildings, limits our ability to characterize archetype parameters stochastically. In individual building modelling, comparable parameter uncertainty problems are typically solved through calibration methods based on metered demand data. However, given the access to energy data is heavily restricted, very little research has focused on developing UBEM calibration methods. In this section, a brief review is presented of previous research efforts regarding the application of uncertainty modeling and calibration in BEM, and how they might translate into UBEM workflows. The general goal of the chapter is to address the research hypotheses regarding the reliability of UBEM, and demonstrate that it is possible to increase their accuracy by introducing calibrated stochastic parameters. Specific research objectives are to:

- Develop a method for the calibration of stochastic archetype parameters with a limited amount of metered energy data using Bayesian statistics.
- Evaluate the accuracy of the method, and compare it with that of existing deterministic and stochastic archetype characterization methods for a neighborhood of several hundred buildings.
- Validate the proposed calibration method for a separate, nearby neighborhood.

### *4.1.1 Stochastic archetype parameters and occupant behavior*

As discussed in Chapter 2, archetype descriptions that use solely deterministic parameters are unable to reproduce the diversity of demands found within the population they represent. Since an archetype's purpose is to represent a whole population of buildings, individual parameters will be inevitably uncertain. Even in a case in which all structures represented were identical in terms of materials and systems, or their differences were small enough to be irrelevant in an UBEM, different building occupants will use the building differently. To account for this variety, archetypes need to be characterized in a *stochastic* way, defining unknown parameters as probability distributions [68]. The use of uncertainty modelling techniques to deal with unknown parameters has been extensively addressed in BEM. Their study started with the work of Iain Macdonald identifying which uncertainties are intrinsic to simulation engines such as EnergyPlus or ESPr [126,127] as well as how input variable uncertainties would propagate through the simulation algorithms. Since then, researchers have explored their application for both building retrofit [25] and design purposes [88,89], in an effort to understand how uncertainty in simulation results can be understood and applied by decision makers. Research has also focused on modeling specific sources of uncertainty, from the weather [128] to HVAC systems [129], and on implementing computational toolsets to allow modelers to combine multiple uncertainty types in a BEM, such as the GURA-W tool developed at Georgia Tech [130], which includes a library of standard parameter distributions and sampling functions compatible with EnergyPlus. All of these methods require the definition of uncertainty distributions for model variables, either based on empirical or expert assumptions, which the modeler can choose based on the available information for a specific building. However, it remains unclear how to effectively apply them at the urban level, where they are limited by a lack of data and the high computational cost of running multiple simulations for each building.

Occupant behavior related parameters, are stochastic in nature, and hence are particularly relevant when considering uncertainty sources in a BEM or an UBEM. They also have a decisive impact on the energy consumption of a building, particularly in residential cases where real demands can differ significantly in physically similar buildings [131–133]. Given the variety of factors that affect occupant behavior including user preferences, personal schedules, or number of appliances, these inputs have traditionally been simplified in simulation through the combined use of hourly diversity schedules and peak values. Although useful in early stages of a model, this deterministic technique cannot represent the stochastic nature of occupant related loads. Extensive research has hence focused on combining occupant monitoring data with probabilistic methods [134,135], using data obtained from long term monitoring, time use surveys [136], or travel surveys [137]. While deterministic schedules are appropriate for annual demands, stochastic models perform better in the analysis of hourly peaks or load diversity [138].

In UBEM, when analyzing the annual average or total demand for a district, occupant behavior does not typically have a large effect [139] and can be characterized deterministically based on correlations with demographic factors [77]. Although such methods add some specificity to archetypes, they fail to capture the real diversity in demands. For such purposes probabilistic approaches are more adequate. Stralzka et al [68] showed that introducing normally distributed heating set points in a deterministic UBEM for 300 residential houses achieved a significant improvement in accuracy, and He et al [140] justified the need for stochastic occupancy models for urban hourly load analysis, showing that single deterministic schedules produce unrealistic demand peaks. Although better occupant modeling methods are needed in UBEM, especially for calibration, there is no consensus about how to implement them.

### *4.1.2 Energy model calibration in BEM and UBEM*

Since the purpose of UBEMs and of bottom up urban models in general, is to estimate building demands individually, a calibration step using measured energy data at that scale is necessary to achieve confidence in its predictions. In the field of individual building energy simulation, extensive research has focused on implementing calibration methods to match model results with metered demand at annual, monthly, hourly and sub hourly scales. Such well-established methods can be classified in two main groups: *Optimization* and *Bayesian* calibration [141]. Both are based on the manipulation of a vector of input parameters, with the objective of reducing one or more error metrics against the real data. It remains unclear however, how these methods are to be applied in UBEM, where the large scale of the models presents additional limitations in energy data access and computational efforts.

UBEM calibration can not only be performed at multiple temporal scales, but also at different levels of spatial aggregation, by building, block, district, etc. The appropriate level will depend on the purpose of the model (e.g. energy efficiency policy vs supply planning) and, more importantly, to the measured energy data available to the modeler. Since measured energy demands for individual buildings are rarely accessible, UBEM validation and calibration in the past has mostly relied on single aggregate annual demand values for complete districts. Since aggregate errors for large populations of buildings tend to average out, validation studies have reported relatively low errors, in the 1-15% range. However, it does not guarantee any accuracy at smaller scales: The review presented in Chapter 2 found reported errors in individual building energy prediction in urban models errors up to 15 times higher than for the aggregate. To address this problem, intermediate calibration scales such as the zip code level [96] have been proposed. However, the question remains how to calibrate non-deterministic parameters. I will show in the following that Bayesian calibration techniques are particularly well suited for this purpose.

Bayesian inference is a statistical inference method in which Bayes Rule is used to update the probability for a hypothesis as more evidence becomes available. Bayes Rule relates the conditional probability of an event given another with their prior individual probabilities [142]. Kennedy and O'Hagan and others have proposed the use of Bayesian inference in computer model calibration, in order to address uncertainty coming from a variety of sources: Input parameters, model or code inadequacy, or observation errors [143]. This calibration technique can reduce the uncertainty of parameters characterized as distributions, and is therefore better suited for UBEM calibration than optimization methods. It has been successfully used in single building energy modeling, by defining prior distributions for select relevant parameters and using measured data to reduce their uncertainty [25]. At a larger scale, Heo at al suggested its use for large portfolios of buildings [144], while Booth et al [26,145] proposed extending Bayesian calibration to an urban context by applying it to clusters of buildings of the same type, and tested the approach on a set of 35 apartments using a steady state model. Similarly, Kim et al [146] used Bayesian calibration to estimate the distribution of four parameters and a "lifestyle factor" for 2,182 new construction apartments in Korea. This chapter explores the expansion of these methods for the improvement of UBEM archetypes characterized through stochastic parameters.

## 4.2 Methodology

In order to achieve these research objectives, a methodology is developed in the following sections for the definition, implementation and validation of a new Bayesian approach to the calibration of stochastic archetype parameters in UBEM. The calibration method is described in detail in section 4.2.1, while its limitations and requirements are presented in the results section of this chapter. For its comparison and validation against existing approaches, an UBEM model is generated for a residential district case study in Kuwait City. The steps followed in its development and analysis are summarized in Table 4-1, and described in detail in the following sub sections 4.2.2 to 4.2.5.

*Table 4-1: Workflow for the comparison of archetype definition methods in Kuwait's case study*

| Analysis step | Methodology |
|---|---|
| 1 Urban data gathering | All available information for the selected district in Kuwait City is gathered in collaboration with the local municipal government, including building geometry information, building properties and metered demand data. (Section 4.2.2) |
| 2 Archetype characterization | Building archetypes are classified and characterized based on the available data using three characterization methods of increasing detail level: (Section 4.2.3)<br>**A** Deterministic, based on literature data<br>**B** Deterministic, based on literature and building data<br>**C** Probabilistic, based on literature and building data |
| 3 UBEM model generation | A full urban building energy model is developed for Areas 1, 8, and 9 within the district assuming archetype definition schemes A, B and C. (Section 4.2.4) |
| 4 Archetype Bayesian calibration | Key occupancy related parameters are calibrated using the Bayesian approach (Section 4.3.1) based on a learning set of metered data from Area 8. Probabilistic archetypes are updated and modeled in an additional characterization scheme:<br>**D** Probabilistic, calibrated with energy data. |
| 5 Energy demand simulation | Characterization schemes A, B, C and D are simulated using EnergyPlus. For probabilistic cases C and D, parameters are sampled using Latin Hyper Cube. |
| 6 Comparison and validation | Simulated EUI distributions for all four scenarios are compared against metered data in Area 8. Later, calibrated parameters from Area 8 are validated against metered data in Areas 1 and 9. (Sections 4.3.2 / 4.3.3) |

### *4.2.1 A Bayesian approach to archetype calibration*

As discussed in the introduction, calibration techniques currently applied in BEM are not well suited for their implementation in UBEM. It is unrealistic to expect the estimation of "correct" input parameter values for every building in a city, given the enormous amount of energy and building data that would be required for validation. Even if such a gargantuan task were to be undertaken, the resulting parameter values would not be particularly useful for planning purposes, because first, they would only be representative of a particular moment in time, and second, the resulting model resolution would never be used for decision making by a municipality. Instead, this dissertation introduces the idea of calibration at the scale of the "archetype". In such scenario, parameters would be defined stochastically, and the reduction of uncertainty in calibration would apply to all buildings within the archetype's population.

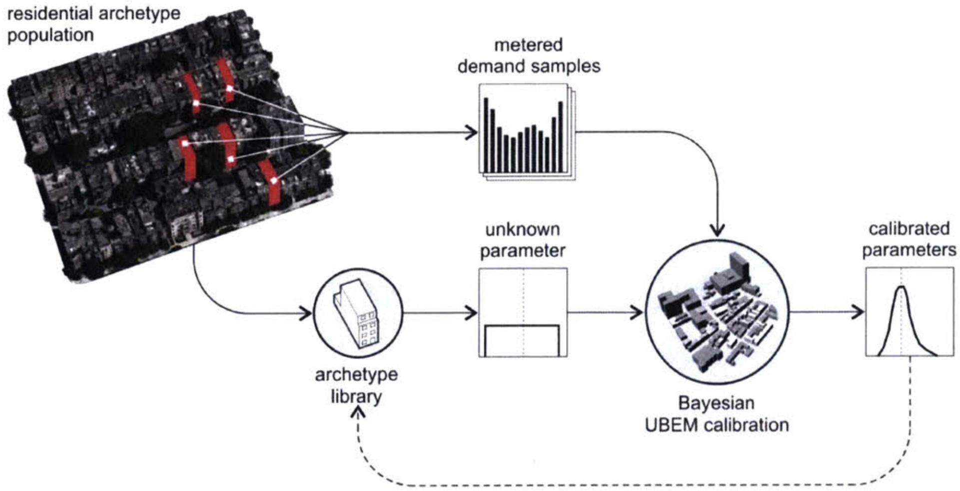



*Figure 4-1: Bayesian calibration conceptual approach*

To achieve it, this section proposes a Bayesian approach to the calibration of stochastic archetype parameters for UBEM. This requires a statistically representative sample of metered buildings from the population of a particular archetype and an UBEM simulation model (Figure 4-1). The method assumes that from all simulation parameters to be defined in the archetype under consideration (constructions, systems, loads, etc.), a subset has been identified for calibration as particularly relevant, and unknown to the modeler. The remaining parameters are assumed to be known, and defined deterministically. As with any other calibration approach, the selection and range of input parameters involves a certain degree of educated guessing as to what parameters are most likely unknown and relevant to describe actual energy use in buildings. A variety of sensitivity analysis and parameter screening techniques are available for that purpose, which have been adapted for their use in building energy modeling [147,148].

When a single building in the model is considered, then the selected input parameters defined as distributions, can be grouped in a vector $\boldsymbol{\theta}$, while the remaining deterministic parameters are grouped in a vector $\mathbf{x}$. Given those two sets, the simulation model can be described by the notation $\mathbf{y} = G(\boldsymbol{\theta},\mathbf{x})$, where G is the energy simulation algorithm, and $\mathbf{y}$ is the vector of model energy demand outputs, which can be defined at multiple temporal scales (annual, monthly, hourly). As previously described, the objective of any calibration procedure is to minimize the difference between the demand predictions of the model and the real metered demand. In this model definition, given a vector of metered demand values $\mathbf{d}$, the model can be calibrated by varying the unknown probabilistic parameters $\boldsymbol{\theta}$ such that the error between simulated outcomes ($\mathbf{y}$) and observed outcomes ($\mathbf{d}$) is minimized.

As discussed in the introduction, a variety of calibration methods for BEM have been introduced in the last decade that take advantage of Bayesian statistics techniques to reduce the modeler's uncertainty regarding input parameters. In Bayesian calibration it is necessary to characterize the initial uncertainty for each parameter with a "prior distribution", which in the simplest scenario can be assumed uniform. According to Bayes Rule, the posterior joint probability distribution of uncertain parameters **θ**, given observed data **d**, is proportional to the specified prior probability of **θ**, multiplied by the probability (In this case, the likelihood) of observing **d** given **θ** (Equation1):

$$P(\boldsymbol{\theta}|\boldsymbol{d}) \propto P(\boldsymbol{\theta})\, P(\boldsymbol{d}|\boldsymbol{\theta}) \qquad (1)$$

This formulation and application of Bayes Rule is based on Kennedy and O'Hagan definition [143], and has been applied in BEM calibration by Heo et al. [25]. In simpler engineering calculations, it might be possible to express the conditional probability of a set of observed measurements - $P(\boldsymbol{d}|\boldsymbol{\theta})$ - through an explicit function and known parametric distribution shapes, so that the problem can be solved analytically. However, since dynamic thermal processes in buildings are complex enough to require the use of a simulation engine, no such function is available to define demands for a particular parameter vector **θ**. Alternatively, it is possible to take a "frequentist" approach, and define this missing probability as a likelihood, quantified as the proportion of a large set of simulated cases in which a particular demand is predicted. In BEM, metered data over multiple days or years can provide a large enough observed sample, but the size of an UBEM and the general lack of metered data require a different approach.

In the archetype calibration approach proposed, instead of calibrating one building based on a large sample of different demand observations, an archetype is calibrated based on a representative sample of buildings with individual demand observations. Conceptually, the proposed method falls within the larger umbrella of "Building energy epidemiology" [82], and focuses on learning from a few existing buildings to understand better the characteristics and occupant behavior tendencies in the larger building stock. The likelihood $P(\boldsymbol{d}|\boldsymbol{\theta})$ is obtained from an aggregate error analysis over the sample building population. If $\varepsilon(\, \boldsymbol{y}(\boldsymbol{\theta}), \mathbf{d}\, )$ is the relative error between the simulation outcome $\boldsymbol{y}(\boldsymbol{\theta})$ and the observed outcome **d** for a particular building, and $\alpha$ is the maximum acceptable error between the two, then the likelihood of that value for **θ** being true can be defined as shown in Equation 2:

$$P(\boldsymbol{d}|\boldsymbol{\theta}) = \begin{cases} 1 & if \;\; \varepsilon(\boldsymbol{y}(\boldsymbol{\theta}), \boldsymbol{d}) < \alpha, \\ 0 & otherwise \end{cases} \qquad (2)$$

The posterior probability distribution $P(\boldsymbol{\theta}|\boldsymbol{d})$ is then proportional to the set of all vectors **θ** that are accepted according to that function. The number of accepted vectors can be 0, 1 or more, meaning that multiple solutions are accepted with equal probability and that a zero implies that the parameters chosen cannot explain the measured value. This value can be obtained for each building in the sample, and the accepted vectors **θ** of all of them for the archetype under calibration can be combined in one multivariate joint probability distribution$P(\boldsymbol{\theta}|\boldsymbol{d})$. This process is shown in Figure 4-2, where the vector **θ** represents samples from prior distributions and **θ'** from the posterior distribution.

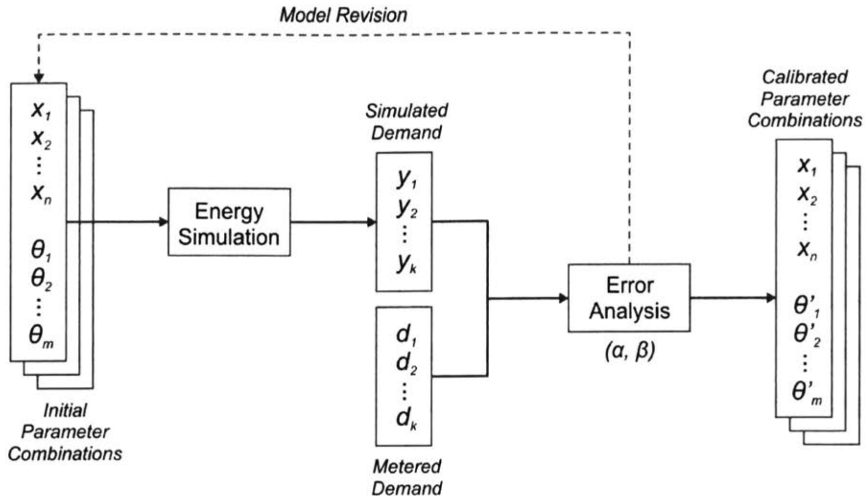



*Figure 4-2: Bayesian calibration method diagram*

It is important to highlight that, as defined above, the calibration method is assuming that the only uncertainty in the model is coming from unknown building parameters. Generally, the calibration of an energy model needs to take into account two other sources of uncertainty: The potential "observation error" from the metered data itself, and the intrinsic errors in the simulation engine, which are the result of the way the engine simplifies thermal processes [143]. The approach introduced here accounts for these typically small uncertainties by assuming they are included within the acceptable error level $\alpha$, but in a more general formulation of calibration they should be defined as stochastic parameters as well.

Additionally, and given that the method relies on a "large enough" number of buildings to generate likelihoods, its use is not appropriate with archetypes representing very unique and distinct buildings (i.e. hospitals, prisons, etc.), or very small populations. It is however appropriate for the calibration of standard residential and commercial buildings. The question of how many buildings represent a "large enough" sample is key, as it relates directly with the effort required in its application. . However, it is also a fairly complex question, since the right sample size will depend on the actual size of the population to be represented, the maximum calibration error considered acceptable, the type of building under consideration, and ultimately the difficulty in accessing the data. While this chapter focuses on the definition and validation of the calibration method itself, future research will have to explore the issue of archetype sampling in more detail. The complete calibration procedure in its simplest form, conceived for the improvement of UBEM archetypes, can be applied through the following steps:

1 Parameter Definition: First, $m$ unknown parameters in $\boldsymbol{\theta} = [\theta_1, \theta_2, \ldots, \theta_m]$ are selected (through screening, sensitivity analysis, etc.) and defined through their prior distributions, which will be uniform when no empirical information is available.

2 Parametric Simulation: A parametric analysis is performed for each building in the sample through UBEM simulation, taking each possible combination of values for $\boldsymbol{\theta}$.

3 Error Quantification: The simulated energy use for each parametric combination and each building is compared to the metered demand for the building and a relative error $\varepsilon$ is calculated. If $\varepsilon$ is less than a given threshold, $\alpha$, the underlying parametric combination, vector $\boldsymbol{\theta}$, is selected as a "valid" solution for that particular building.

4 Test of Assumptions: The ratio of buildings R for which at least one valid solution was found is calculated. If R is smaller than an acceptable percentage of the sample ($\beta$), both the components of $\boldsymbol{\theta}$ and the model should be revisited in Step 1. Buildings which cannot be explained are analyzed in an effort to identify variables unaccounted for, or irregularities in the buildings.

5 Distribution generation: All accepted input vectors $\boldsymbol{\theta}'$, are combined in a multivariate joint probability distribution $P(\boldsymbol{\theta}') = P(\theta'_1,\theta'_2,\ldots,\theta'_m)$.

6 Random Sampled Simulation: : Using the joint probability distribution, $P(\boldsymbol{\theta}')$, the calibrated UBEM can be used to model the energy use distribution in a neighborhood by simulating each building multiple times based on randomly sampling combinations of parameters from $P(\boldsymbol{\theta}')$. The resulting frequency distributions of energy use for individual buildings are combined for all buildings leading to a neighborhood-wide energy use distribution.

*4.2.2 Kuwaiti case study*

The above laid out method was originally applied to a neighborhood in Kuwait as part of a multi-year research effort between MIT, Kuwait University (KU) and the Kuwait Institute for Scientific Research (KISR). The study of residential building energy use is of particular relevance in Kuwait: 45% of the country's fuel consumption is dedicated to the generation of electricity, mostly in gas or oil plants and – according to the Ministry of Energy and Water – 60% of that electricity is used in the residential sector [149]. More importantly, in such a cooling climate, AC accounts for more than 60% of the residential use and 85% of the peak consumption. This distribution makes the analysis of residential thermal demands especially relevant. Currently the Kuwaiti government is developing its goals for reduction of GHG emissions by 2030, planning to cover 15% of demands from renewable sources and to reduce building demands by another 15%. However, these goals are especially challenging in the present situation, since residential cooling demand peaks can at times exceed grid capacity during the summer, while the demand for new residences keeps increasing with a government housing waitlist of over 100,000 families and growth rate of 3%.

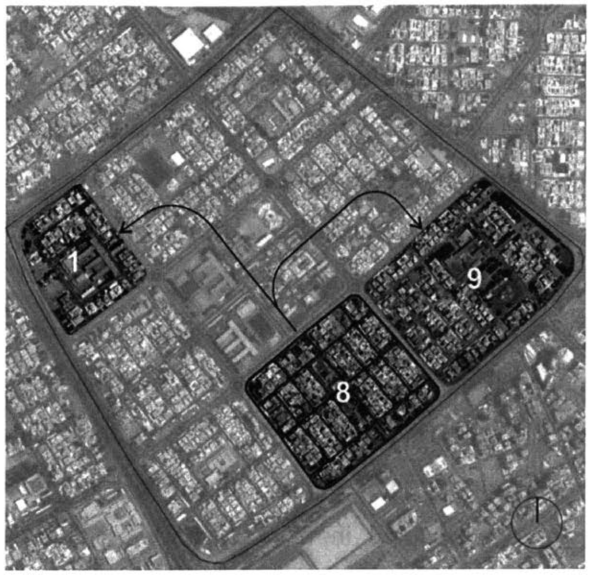



*Figure 4-3: AlQadisyah district and metered areas 1/8/9*

The residential district of AlQadisyah was selected for the evaluation of different urban archetype definition approaches, in collaboration with KU and KISR. AlQadisyah is a district mostly formed by 2 to 3 stories villas or small apartment buildings, developed initially in the 1960s and with an area of approximately 1.6 km2. It is organized in 9 distinct areas, with the central Area 5 containing most services and commercial buildings, and the remaining 8 comprising between 50 to 200 residential structures (see Figure 4-3). AlQadisyah is representative of the residential fabric in the city, with a majority of villas built as government provided housing. According to their year of construction, the villas in the neighborhood can be grouped into three main periods depicted in Figure 4-4: (1) government housing built between the 19060s and 80s in some cases retrofitted in the 1990s or 2000s represents which 48% of the district. (2) villas, private or government sponsored, built in the 80s and 90s under the 1983 Energy Conservation code [150] which represent 42%; (3) recent structures built after the 2010 Energy Code [151] accounting for a 10%.

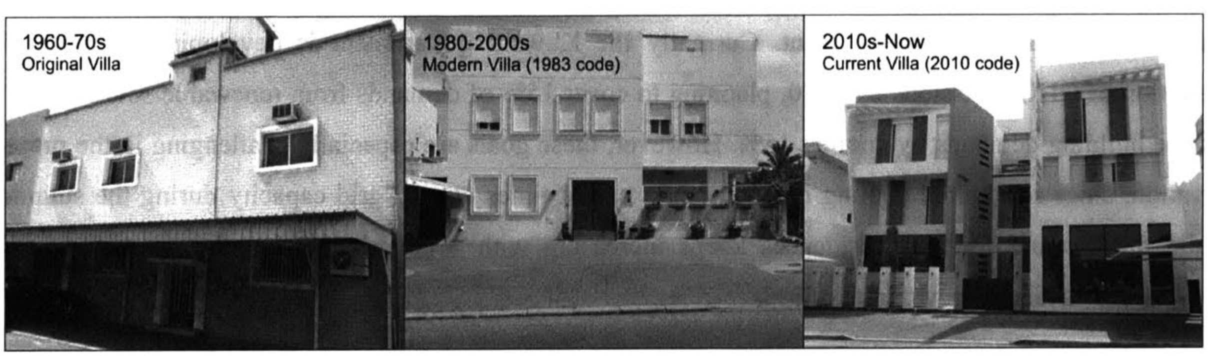



*Figure 4-4: Examples of residential buildings by period of construction*

During March 2014 an extensive data gathering campaign was conducted by the author, in collaboration with KISR and Kuwait University (KU) for Areas 1, 8 and 9 of AlQadisyah which included GIS information from the city, building documentation and metered energy demands. Regarding geometric information, building footprint polygons were provided in the form of a GIS shapefile by the city, as well as a digital elevation map for building heights. For further definition of the model, a site survey and neighborhood walkthrough was performed in the three areas which included photographic documentation of Window to Wall Ratios (WWR) and number of stories. In addition, local experts were consulted and buildings both under construction and demolition were visited, in order to characterize building properties and define vintage based archetypes (Figure 4-5a).

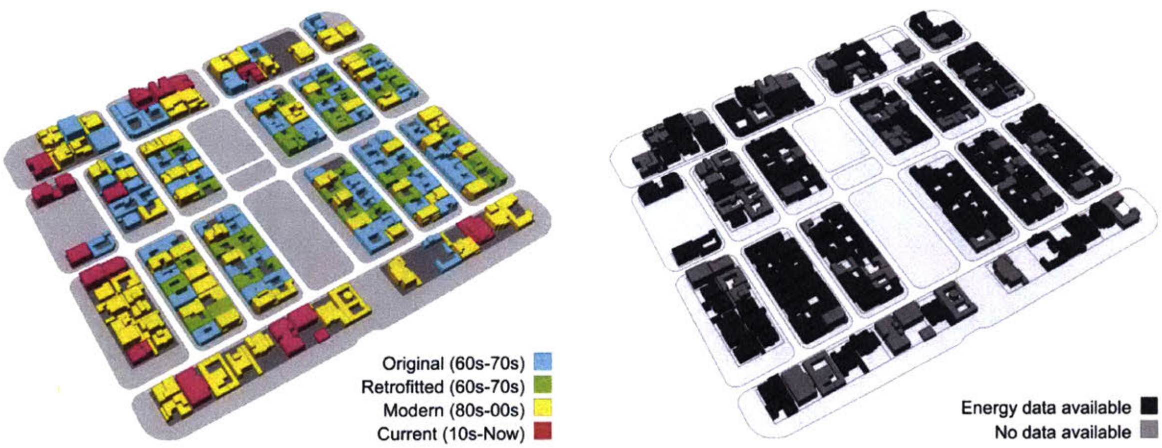



*Figure 4-5: Area 8 buildings classified by vintage (a) and energy data availability (b)*

Regarding energy consumption for calibration, metered annual demand for 2013 was gathered for 172 buildings in Area 8, 133 in Area 9 and 31 in Area 1 (see Figure 4-5b for data availability in area 8). After eliminating data points in which data quality was uncertain (i.e. very low EUIs indicating only partial yearly occupation or non-existing buildings), a set of 164, 129 and 30 buildings were selected for Areas 8, 9 and 1, respectively. Weather data for air temperature, humidity and solar radiation were gathered for the same period from a nearby weather station. For the purposes of this study, and in order to use similarly sized samples, Areas 9 and 1 demands were combined in a single dataset including 159 metered buildings, referred to from now on as Area 9/1. Area 8 is used as the "training" dataset for calibration Area 9/1 is used for validation. The Energy Use Intensity (EUI) for each building was calculated based on built floor area and resulting distributions for Areas 8 and 9/1 are shown in Figure 4-6. Both cases showed very similar mean EUIs of 209 and 199 kWh/m2 respectively, with a global minimum of 66 kWh/m2 and a global maximum of 444 kWh/m2. Table 4-2 provides a summary for both distributions, including their mean, minimum and maximum values, and $10^{th}$ and $90^{th}$ percentiles as a measure of statistical variation.

*Table 4-2: Statistical values of EUI distributions for Areas 8 and 9/1 in kWh/m2*

| District Area | #Buildings | Mean (kWh/m2) | $P_{10}$ (kWh/m2) | $P_{90}$ (kWh/m2) | Minimum (kWh/m2) | Maximum (kWh/m2) |
|---|---|---|---|---|---|---|
| Area 8 | 164 | 209 | 109 | 304 | 81 | 444 |
| Area 91 | 159 | 199 | 120 | 303 | 83 | 366 |

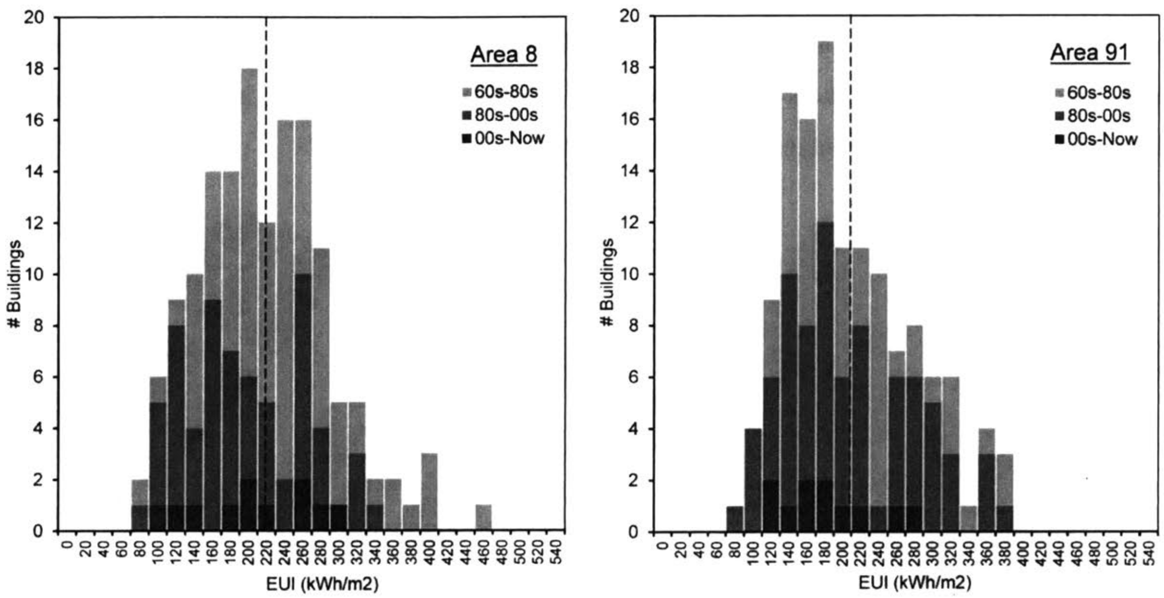



*Figure 4-6: EUI distributions for Areas 8 and 9/1 by construction period*

### *4.2.3 Archetype characterization*

Four different archetype definition approaches are implemented as introduced at the beginning of this methodology. In methods A and B parameters are defined only deterministically, while in methods C and D select occupancy-related parameters are modeled as uncertain stochastic variables.

<u>Deterministic / Available literature (A)</u>

Method A represents the most basic level of archetype definition in which the only available information about buildings and occupants comes from published literature in the form of research publications, government reports about the built environment and standards. In the case of Kuwait, few publications about residential villas were available. In addition, no building specific data could be gathered. For that reason, buildings were classified using only one archetype (Residential), and hence one building type and one occupant type. Constructions, AC coefficient of performance (COP), set point temperatures, and internal loads were defined deterministically according to published residential energy models [152–154] and requirements from the 2010 Energy Code [151]. Finally an average WWR of 20% was assumed throughout the model. See Tables 4-3 and 4-4 for a summary of parameter values.

*Table 4-3: Summary of archetype building parameters for methods A, B, C and D*

| | | | Deterministic | | Probabilistic | |
|---|---|---|---|---|---|---|
| **Parameter** | **Units** | **Period** | **Literature** | **Building Data** | **Occupants** | **Calibrated** |
| Wall U | W/m2K | 60s-70s (O) | 0.62 | 2.53 | 2.53 | 2.53 |
| | | 60s-70s (R) | | 2.53 | 2.53 | 2.53 |
| | | 80s-00s | | 0.62 | 0.62 | 0.62 |
| | | 10s-Now | | 0.32 | 0.32 | 0.32 |
| Roof U | W/m2K | 60s-70s (O) | 0.53 | 1.56 | 1.56 | 1.56 |
| | | 60s-70s (R) | | 0.53 | 0.53 | 0.53 |
| | | 80s-00s | | 0.53 | 0.53 | 0.53 |
| | | 10s-Now | | 0.40 | 0.40 | 0.40 |
| Glazing U (SHGC) | W/m2K( - ) | 60s-70s (O) | 2.89 (0.76) | 5.96 (0.86) | 5.96 (0.86) | 5.96 (0.86) |
| | | 60s-70s (R) | | 2.89 (0.76) | 2.89 (0.76) | 2.89 (0.76) |
| | | 80s-00s | | 2.89 (0.17) | 2.89 (0.17) | 2.89 (0.17) |
| | | 10s-Now | | 2.33 (0.65) | 2.33 (0.65) | 2.33 (0.65) |
| Infiltration | ach | 60s-70s (O) | 0.5 | 0.8 | 0.8 | 0.8 |
| | | 60s-70s (R) | | 0.5 | 0.5 | 0.5 |
| | | 80s-00s | | 0.5 | 0.5 | 0.5 |
| | | 10s-Now | | 0.3 | 0.3 | 0.3 |
| Cooling COP | - | 60s-70s (O) | 2.4 | 2.4 | 2.4 | 2.4 |
| | | 60s-70s (R) | | 2.4 | 2.4 | 2.4 |
| | | 80s-00s | | 2.4 | 2.4 | 2.4 |
| | | 10s-Now | | 2.9 | 2.9 | 2.9 |
| WWR | - | All | 0.20 | By building | By building | By building |

Deterministic / Specific building data (B)

A more advanced classification of archetypes requires building by building audit information, combined with a deeper knowledge of local construction practices. Following this approach in method B, buildings were further divided in four archetypes based on the four periods discussed in Section 3.1 and still a single occupant type. The resulting archetypes are: Original villas 60s-80s, retrofitted villas 60s-80s, villas 90s-2000s and villas after 2010. The further characterization of parameters was developed in collaboration with KISR and KU researchers, based on two site visits in the neighborhood developed in 2014. The team documented wall and roof materials, glazing systems and AC equipment in a group of 5 villas including already built, under construction, and in demolition structures. Window to wall ratios (WWR) for each building were individually assessed through photography analysis. In addition, detailed occupancy, plug loads, and lighting power density (LPD) schedules were developed by residential room type based on a survey of 50 similar residences [154] and average room sizes for government provided model residences [155], in order to refine the generic values in method A (Tables 4-3 and 4-4).

Stochastic / Uncalibrated occupancy parameters (C)

The selection of particularly relevant and uncertain parameters in an energy simulation model is a complicated task, which depends on the purpose of the model, the certainty about the remaining parameters and the building type. For that reason, before introducing uncertainty for some input parameters in an UBEM archetype, it is advisable to perform a sensitivity analysis of the model based on reasonable value limits for each parameter considered. Once such parameters are selected, probability distributions have to be assigned to each one based either on expert knowledge, literature or survey data. As described in the introduction, occupant-related parameters are especially difficult to model and almost always unknown to the modeler, while parameter related with the building itself are easier to document through energy audits or building certificates. If the later are fairly well documented, as is the case of AlQadisyah, then the differences between simulated and measured EUIs can mostly be explained by uncertainties in occupant behavior. This is only true if buildings are constructed according to their design specifications and code requirements, and might represent a source of uncertainty as well.

Given the reduced variety of construction typologies and systems in the district, for the purposes of this work only occupant related parameters were modelled probabilistically, while the 4 archetypes defined in case B were used for characterizing buildings deterministically. The decision was based on a simplified sensitivity analysis applied to an average-sized building by archetype, in which the effect in the simulated EUI of 10-30% variations in envelope U values, cooling COPs and infiltration rates was estimated to remain below a 10% in all cases. The range of variation considered was defined based on available literature and comments from local experts from KISR. Further analysis will be required in future studies to incorporate those parameters as additional uncertainties.

*Table 4-4: Summary of archetype occupant related parameters for methods A, B, C and D*

| | | | **Deterministic** | | **Probabilistic** | |
|---|---|---|---|---|---|---|
| **Parameter** | **Units** | **Floors** | **Literature** | **Building Data** | **Occupants** | **Calibrated** |
| Occupancy (OCC) | occ/m2 | Any | 0.020 | 0.012 | U (0.002,0.022) | Joint Dist. |
| Lighting Power (LPD) | W/m2 | Any | 10.0 | 12.3 | U (4.0,20.0) | Joint Dist. |
| Plug Multiplier (MLT) | - | Any | 1.0 | 1.0 | U (0.4,1.6) | Joint Dist. |
| Plug Power (PLG) | W/m2 | One | | 10.8 | f (OCC,MLT) | f (OCC,MLT) |
| | | Two | 8.0 | 7.8 | f (OCC,MLT) | f (OCC,MLT) |
| | | Three | | 6.3 | f (OCC,MLT) | f (OCC,MLT) |
| DHW Peak Flow | m3/h/m2 | Any | 0.00013 | 0.00013 | f (OCC) | f (OCC) |
| Cooling Set point | °C | Any | 22 | 22 | U (18,26) | Joint Dist. |
| Heating Set point | °C | Any | 18 | 18 | 18 | 18 |

Three base occupant-related parameters were chosen as critical to the variability of the archetype according to the previously referred analysis: Cooling set point temperature in °C (STP), peak installed lighting power density in W/m2 (LPD) and peak average occupancy in occupants/m2 (OCC). Peak plug loads (PLG) and peak hourly domestic how water consumption (DHW) were modelled as linear functions of occupancy as shown in equations 3 and 4, based on deterministic appliance modeling by room for a standard villa. Finally, a fourth uncertainty parameter (MLT) was added as a plug loads multiplier to represent different types of users. Other occupant parameters, namely flowrate due to window operation, window shading operation, and hot water usage per person were defined deterministically. Conversations with local partners revealed that window ventilation in Kuwait residences is almost never used, due to the constant presence of sand dust. Similarly, exterior window shading (common in most residences) stays almost permanently 70-80% closed due to the very high and undesirable solar radiation.

$$PLG(W/m2) = \begin{cases} (7.7 + 260 \times OCC) \times MLT & one\,floor, \\ (4.7 + 260 \times OCC) \times MLT & two\,floor, \\ (3.2 + 260 \times OCC) \times MLT & three\,floor \end{cases} \quad (3)$$

$$\mathrm{DHW}(m3/h/m2) = 0.01083 \times OCC \quad (4)$$

The initial of prior distribution assumed for each uncertain parameter can be assigned a particular shape depending on the available empirical knowledge for the parameter (e.g. uniform, normal, triangular, etc.), with better results the more accurate the distribution. In this case study, given that only simple reference values were available for Kuwait, each one of the four stochastic parameters, OCC, STP, LPD, and MLT, were defined with uniform probability distributions by a minimum and a maximum acceptable value (See Table 4-4). For the purposes of sampling, the uniform distributions were divided using equal step sizes into a parametric grid. Due to constraints of computing power, the number of steps was limited to 5 per parameter (625 combinations per building). Finally, hourly schedules associated with each one of these parameters in the model were defined also deterministically as with case B, because validation at an hourly scale was not possible with the available energy data (only metered annually), and the potential uncertainty associated with them has a negligible impact in the aggregate annual simulated EUI.

Stochastic / Bayesian calibration (D)

In the case of a stochastic archetype characterization, those parameters deemed unknown can be calibrated based on measured energy consumption, so that the shape of their distribution is better known. The Bayesian calibration procedure proposed in 3.2 was applied to the UBEM of Area 8 and 625 parametric simulations were developed for each building. Given the relatively small size of the sample and the fact the resident population in AlQadisyah was relatively uniform regardless of the building age, calibration was performed for the whole area, and not by archetype. The calibration error (α) was defined as the percentage error (PE) in the building annual EUI, with a maximum acceptable value of 5%, based on ASHRAE Guideline 14-2002 recommendations [110] (see Equation 5).

$$\mathrm{PE} = \frac{EUI_{mes} - EUI_{sim}}{EUI_{mes}} \times 100\% \qquad (5)$$

After analyzing the simulation errors according to $\alpha$, the ratio of buildings with at least one accepted parameter combination ($\beta$) resulted in a value of 85%, leaving 26 unexplained buildings. The author decided to take $\beta$ as an acceptable coverage value. The remaining buildings will be revisited in future research to identify the shortcomings of the model. Finally, all accepted parameter vectors were combined in a calibrated joint multivariate distribution. The marginal distributions for the four parameters are presented in Section 4.1. The rest of archetype parameters keep the same values as in methods B and C.

*4.2.4 UBEM simulation and sampling workflow*

For the comparison of methods full energy models were built of the urban case study for areas 8, 9 and 1 of AlQadisiyah. The multi-tool workflow introduced in Chapter 3 was used for that purpose, using a GIS shapefile as a base input for building geometry. Each structure was described by its footprint polygon, its height and number of stories, its WWR, and the name of its archetype. Based on this dataset, multi-zone energy models for all buildings as well as 3D context shading were generated within the CAD environment Rhino 3D [70] and its parametric modeling tool Grasshopper [123]. Simulation parameters for each archetype were stored and implemented in the JSON template library file format previously proposed as a standard for UBEM and BEM model inputs exchange [51]. Finally, archetype data was associated with each building within Grasshopper, and used to generate individual energy models using the Archsim plugin tool [52]. All simulations were developed using EnergyPlus [16]. In addition to the C# applications previously built within Grasshopper for the generation of models and shading calculations, new components were programmed by the author to automate the parametric analysis of buildings and the later sampling parameter distributions.

Regarding the sampling of occupant-related stochastic parameters in methods C and D, both the uniform and calibrated joint distribution were sampled using a Latin Hyper Cube (LHC) approach, dividing the parametric space into 5 areas. The reason of the choice of LHC over simple random sampling was to guarantee a uniform coverage of the parametric space with a reasonable amount of samples per building which could be achieved with the computation resources at hand. Each building was simulated using 100 samples, resulting in 16,400 simulations in area 8 and 15,900 in area 9/1. The size of the sample, in this case 100, was determined by computational requirements in an effort to keep simulation times within an acceptable time. Although this sample size covers a majority of the possible parameter combination values, it necessarily introduces a certain numerical error resulting from those combinations not considered in the simulation. In this case, given the sample size of 100 the standard sampling error of the mean will be proportional to the square root of the sample size (0.10 or 10%) in each building, and was assumed acceptable results were only analyzed in the aggregate of the neighborhood. However, further research needs to be developed with larger sampling sizes to better determine the minimum sample required. The use of a state of the art multicore desktop computer with 16 cores resulted in 4-5 hours of simulation for each Area.

*4.2.5 Comparison and validation of characterization methods*

The simulated energy results from methods A, B, C and D were compared with metered energy demands to understand the accuracy implications of each approach. Given the annual temporal resolution of the observed data, the energy metric chosen for comparison was building EUI in kWh/m2. The purpose of the proposed calibration is to reduce the uncertainty in archetypes and not in individual building models, and to more effectively represent the diversity in real energy demands at a neighborhood scale. For those reasons, the accuracy of the model and its success in reproducing the metered demands was evaluated comparing, not individual demands, but EUI distributions for the analysis area. Four error metrics were chosen to evaluate the similarity between simulated and measured distributions. The percentage error (PE) between the metered and simulated mean EUIs ($\mu$) was used to evaluate the capacity of the model to represent the aggregate and average demands of the district. The PE between the $10^{th}$ and $90^{th}$ percentiles ($P_{10}$, $P_{90}$) for the metered and simulated EUIs was used to analyze how well extreme demands are represented. Finally, the Kolmogorov-Smirnov (KS) test, a nonparametric test of whether two given samples are likely to arise from the same distribution, was used to evaluate the overall similarity in the EUI distribution shape. The KS statistic ($D_n$) is calculated as the maximum absolute difference between the cumulative distribution functions of the two variables, $F(EUI_{mes})$ and $F(EUI_{sim})$, for a number $n$ of data points (Equation 6).

$$D_n = \sup|F_n(EUI_{sim}) - F_n(EUI_{mes})| \qquad (6)$$

For the initial method comparison, these metrics were calculated for each method for area 8, the same dataset used as well for the calibration of probabilistic parameters. For the validation of method D, the calibrated parameters obtained in area 8 from the training datasets were applied for the characterization of archetypes in area 9/1. After obtaining simulated EUIs from the simulation of area 9/1, results were compared with metered data, using the same performance metrics.

## 4.3 Results

The implementation of the previously described methodology, resulted in a total of 102,500 EnergyPlus simulations for the calibration of parameters, plus 49,500 developed in the analysis of cases A to D. The results from cases A, B, C and D for Area 8 are described in detail in the following sections, in terms of the capability to accurately reproduce the measured demands. Last, the calibrated parameter distributions are applied to Area 9/1.

### *4.3.1 Bayesian calibration results*

Based on the error $\alpha$ and minimum ratio $\beta$ defined in section 4.2.1, a calibrated joint distribution for occupant related parameters was generated. Frequencies for the 625 combinations of the four selected parameters (LPD, STP, OCC, and MLT) were characterized following the proposed Bayesian approach in Section 4.2.1. The resulting likelihood showed that a majority of the metered buildings' demands fitted with parameter combinations located in the lower end of the parametric space. Figure 4-7 depicts the calibrated marginal distributions for the four parameters compared to the uniform uncalibrated. It shows how the parameters related to internal lighting and plug loads (LPD and MLT) present differences up to 4% against the uncalibrated distributions, with averages of 11.05 W/m2 and 0.95 respectively. The weighting towards low consumption parameters is even higher in the cooling set point (STP) distribution with a calibrated average of 21 C and a maximum difference of 5% against the uncalibrated case. Only calibrated occupancy (OCC) showed a distinct peak at 0.007 pp/m2.

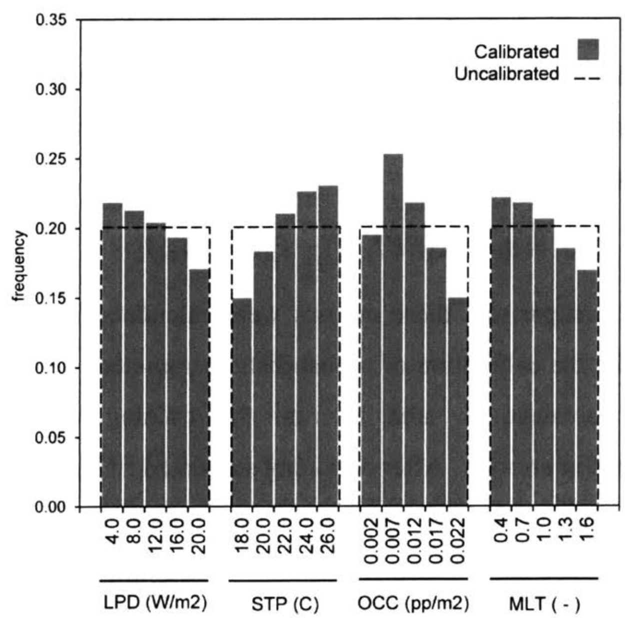



*Figure 4-7: Prior and posterior marginal distributions for calibrated parameters*

It is interesting to observe that in this case the variations in frequency for the marginal distributions, before and after calibration were not particularly large, a fact reflected later in the comparison of results for cases C and D. This can be explained by an already small parametric space of analysis, result of the fairly extensive documentation of typical parameter values for Kuwaiti villas developed as part of the study. Theoretically these resulting distributions are only valid for these buildings and given the deterministic values assigned to the building parameters which were not considered for calibration. However, the validation results in section 4.3.3 will show that they can be extrapolated to other buildings in the city belonging to the same archetype.

*4.3.2 Comparison of Area 8 results by characterization case*

Following the procedure described in Section 3, UBEM models were generated and simulated, applying characterization methods A, B C and D. Figures 4-7 and 4-8 show the simulated EUI distributions on each case compared with the metered distribution, while Table 4-5 summarizes the quantitative error analysis. In method A, the results from the use of a single type archetype present a very small variation in EUI throughout the area, with values ranging between 140 and 220 kWh/m2. This limited diversity is only caused by building shape, size and shading context and it is very far from accurately representing the real EUI distribution. The simulated mean EUI underestimated the real one by a 16%, with errors of 55% and 38% in the 10 and 90 percentiles respectively. The introduction in method B of four archetypes based on the building vintage achieved a much better fit for the mean with a PE of 4%, resulting in an UBEM appropriate for the analysis of aggregate results.

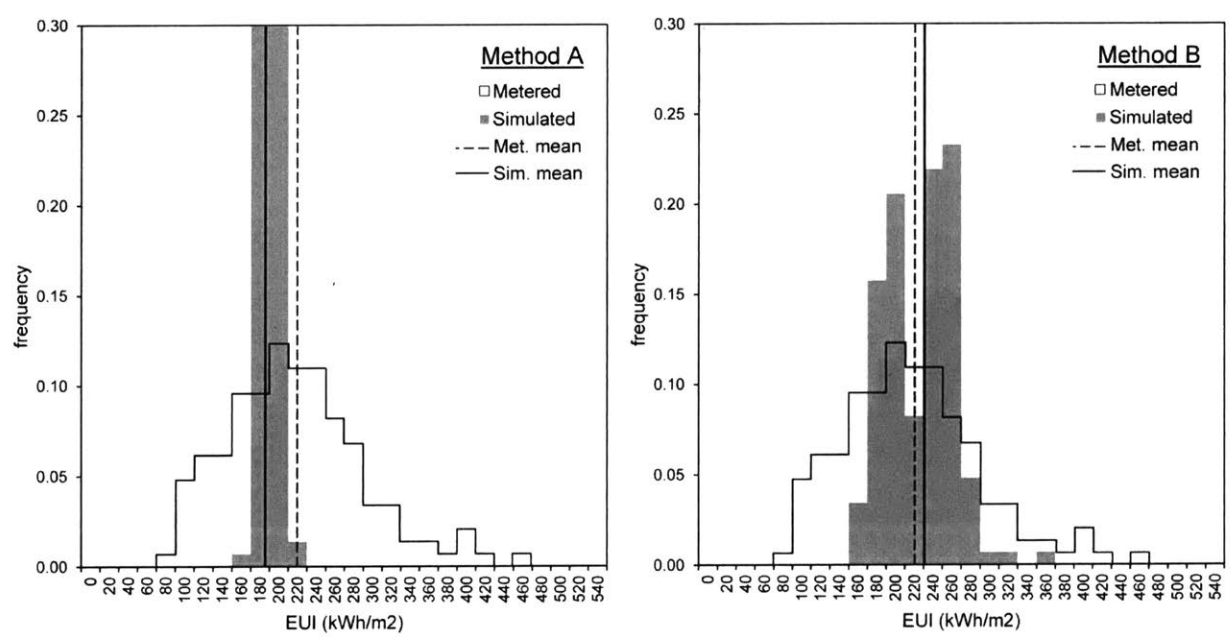



*Figure 4-8: EUI distributions for methods A and B*

However, even when achieving a significant reduction in percentile errors (see Table 4-5) the resulting distribution does not accurately reproduce the measured one. The KS test has a value of 0.24, and the PE for the 10 percentile is still close to 60%. The introduced variety in building types cannot capture the diversity in demands pointing to the need for a more detailed modelling of occupant diversity. Although part of the unexplained EUI diversity could be the result of variations in building characteristics not included in this model, they could not on their own match the more extreme demand cases in the real distribution. In method C occupant diversity is modelled with the use of probabilistic uncalibrated parameters, resulting in four types of buildings and 625 potential combinations of occupant parameters. The simulated EUI distribution (Figure 4-9) achieves a significant improvement over the use of a single deterministic occupant. While the PE of the mean stays equally low (4%), the diversity in demands has increased significantly reducing the PE for the 10 and 90 percentiles to 29% and 4% respectively. The result is a significantly more accurate fit to the measured EUI distribution with a KS value of 0.12 (50% reduction from method B). However, the extremes in the measured distribution, where the most interesting energy users potentially lie, are still not captured, especially in the lower end of the EUI spectrum. The further calibration of occupant related parameters in method D, which results have been described in the previous section, allowed for an even more accurate fit for the measured distribution in the area as depicted in Figure 4-9. Regarding the distribution mean, a PE of less than a 1% was achieved, while the PE for the lower 10 percentile was reduced to a 15% better capturing the concentration of demands below 140 kWh/m2.

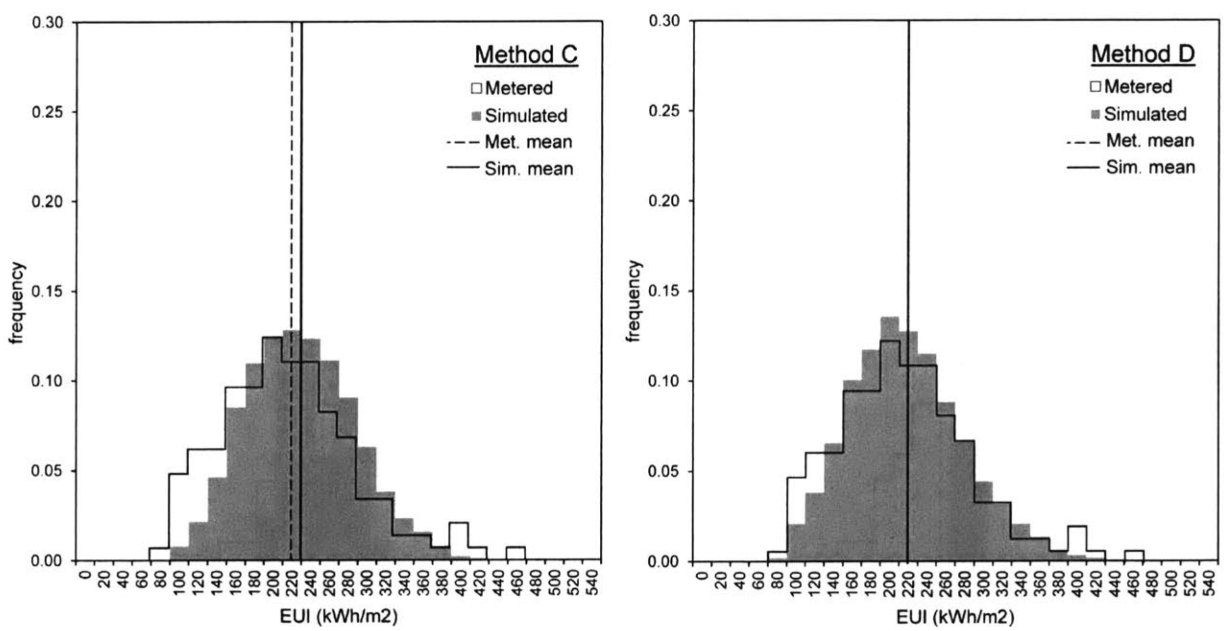



*Figure 4-9: EUI distributions for methods C and D*

The analysis of the distribution shape resulted into a KS value of 0.05 (a reduction of 80% over method C) as summarized in Table 4-5. Although in this particular case both methods C and D do a good job at reproducing the general diversity of EUIs, the Bayesian calibration method used in D was able to really accommodate the measured distribution shape justifying its application. While in this study the improvement was relatively small, the method will become especially useful in cases where initial uncalibrated parameter distributions are particularly wide compared to real ones, or more variables need to be considered.

*Table 4-5: Error metrics summary for Area 8*

| Method | Simulated $\mu$ (kWh/m2) | Simulated $P_{10}$ (kWh/m2) | Simulated $P_{90}$ (kWh/m2) | PE ($\mu$) | PE($P_{10}$) | PE($P_{90}$) | KS |
|---|---|---|---|---|---|---|---|
| A | 177 | 169 | 188 | 0.16 | 0.55 | 0.38 | 0.49 |
| B | 217 | 175 | 256 | 0.04 | 0.60 | 0.16 | 0.24 |
| C | 216 | 141 | 294 | 0.04 | 0.29 | 0.04 | 0.12 |
| D | 209 | 127 | 297 | 0.01 | 0.15 | 0.02 | 0.05 |

### *4.3.3 Validation of the method in Area 9/1*

The results depicted in section 4.3.2 show how the calibration of a certain building population archetype achieves a significant accuracy improvement in UBEM. However, in the case presented parameters were calibrated based on annual energy demand data from the same area 8 in which they were later used for simulation. In order to further validate method D, and demonstrate the usefulness of the calibration of occupant related parameters, area 9/1 was also simulated using four archetypes as well as the resulting calibrated joint parameter distribution obtained from area 8. Results were compared with the metered annual EUI distribution for area 9/1 as shown in Figure 4-10. The simulated EUIs did not produce as close a fit in this case, but still presented acceptable low PE below 5% in the case of the mean (3%) and below 15% for the 10 and 90 percentiles (14% and 7% respectively). The KS value in this case was 0.12, with a 64% reduction over the application of method B for the same area, demonstrating that the calibrated archetype set still reproduces the metered EUI distribution fairly accurately. Nevertheless, the simulation of area 9/1 did not capture the higher concentration of low demands between 80 and 160 kWh/m2. To explore the reasons behind this discrepancy, EUI distributions for both the metered data and the calibrated model were compared by period based archetype (Figure 4-11 and Table 4-6). Given the relatively small number of buildings per distribution when considered at the archetype level, the KS test analysis stops being an effective metric. However, when observing the PE in the mean and percentiles the largest discrepancy appears in buildings from the 60s-70s in their original state were metered demands present significantly lower values than those resulting from the calibrated model. In this case the PE in the mean goes up to 26% with a lower percentile error of 45%.

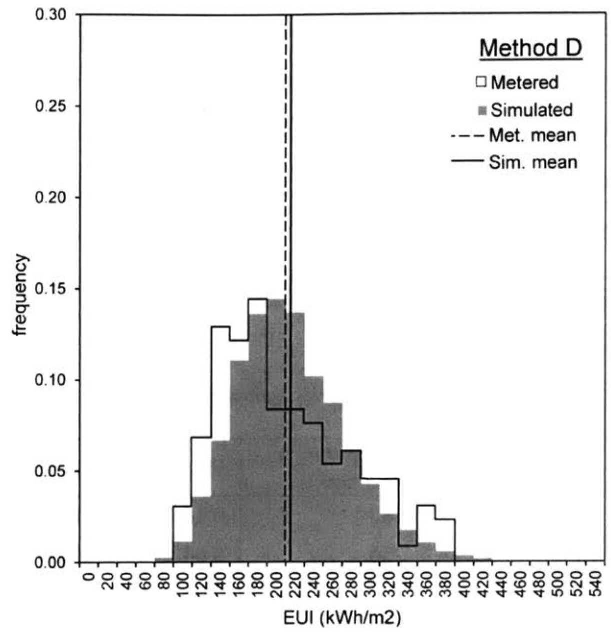



*Figure 4-10: Area 9/1 EUI distributions for method D*

Since the calibration of parameters conducted in area 8 was performed at the scale of the district and not by archetype, the different distribution of buildings by archetype and between areas 8 and 9/1 was identified as a possible cause for the inaccuracies depicted in Figure 4-10. The revision of archetype distributions showed that only 23% of buildings in areas 9-1 belonged to the first archetype against a 34% in area 8. In addition, the metered mean in area 8 for this vintage was 227 compared to 199 in area 9/1. These differences question the validity of the calibration in smaller groups of buildings, an expected result since the calibration was only performed in the aggregate, and points to a need for further validation with a larger dataset. Regardless, the achieved results in Area 9/1 still showed a significant improvement in model accuracy, and suggest that a relatively small sample of buildings (100-200) might be sufficient to characterize the larger population of residential villas in Kuwait City. This is only true of course if it is assumed that the resident mixture in AlQadisyah is representative of all residents of similar buildings, a fact that would have to be validated with a statistical analysis of socio-economic conditions by neighborhood based on census data.

*Table 4-6: Error metrics summary for Area 9/1 method D*

| Population | Simulated $\mu$ (kWh/m2) | Simulated $P_{10}$ (kWh/m2) | Simulated $P_{90}$ (kWh/m2) | PE ($\mu$) | PE($P_{10}$) | PE($P_{90}$) | KS |
|---|---|---|---|---|---|---|---|
| Full Area | 205 | 136 | 283 | 0.03 | 0.14 | 0.07 | 0.12 |
| 60s-70s (O) | 247 | 178 | 326 | 0.24 | 0.45 | 0.06 | 0.39 |
| 60s-70s (R) | 225 | 156 | 302 | 0.11 | 0.22 | 0.02 | 0.26 |
| 80s-00s | 187 | 130 | 248 | 0.06 | 0.13 | 0.19 | 0.16 |
| 10s-Now | 164 | 107 | 229 | 0.16 | 0.01 | 0.17 | 0.11 |

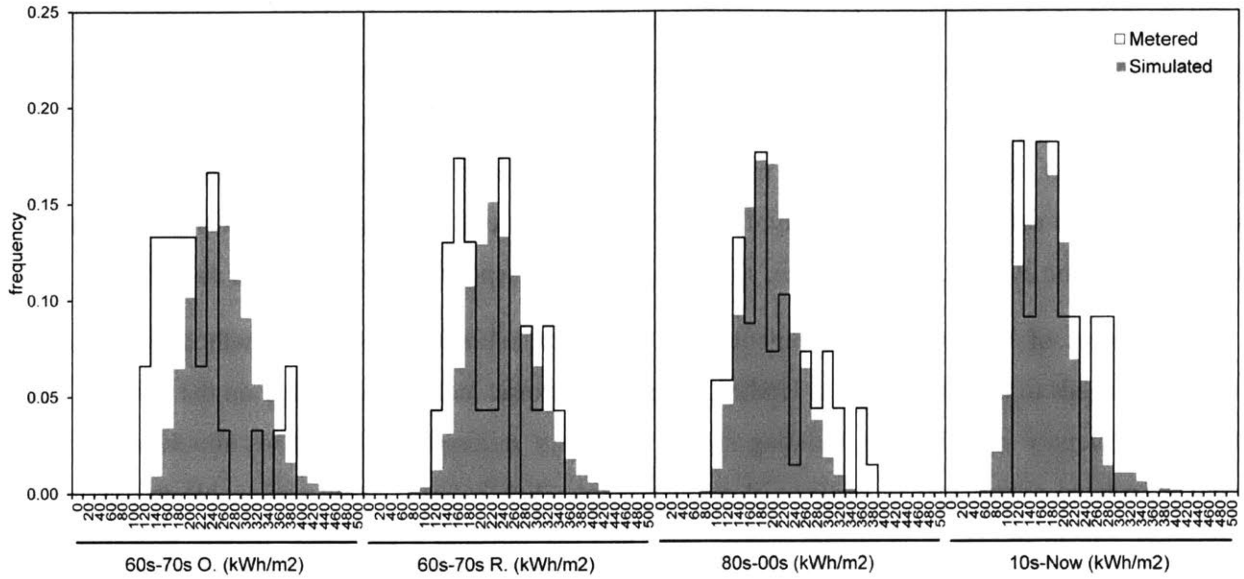



*Figure 4-11: Area 9/1 EUI distributions by archetype*

## 4.4 Discussion

Based on the previously described results, this section discusses the value of the proposed calibration approach in UBEM and the relevance of stochastic parameter characterization in archetype modeling.

### *4.4.1 Selection of stochastic archetype parameters*

This work has presented three available methods for characterizing UBEM archetypes, and proposed an archetype parameter calibration approach, applied to four occupant related parameters as described in Sections 4.2 and 4.3. The results have shown that for this case study the goodness of fit of the aggregate distribution of EUIs was significantly improved, even over an uncalibrated stochastic approach, and that the calibrated archetypes can successfully be applied to similar urban areas, with the sampling reservations indicated above. These findings are encouraging. However, a critical reader might question the assumption that the four chosen occupant parameters are responsible for all uncertainties in the model, and thus suffice to explain differences to measured data. Indeed, other typical unknown parameters assumed constant in this case study such as infiltration rate or cooling COP are most likely to be also partially responsible for the discrepancy between modeled and measured data. Rather than taking the resulting probability distributions for the different occupancy descriptor literally, the reader may rather think of them as a proxy for a larger set of variables.

For this manuscript, as a proof of concept, the author limited the method to a computationally manageable number of variables, with those chosen being, for this particular case, most relevant in the characterization of the real EUI distributions. In future applications, extensive parameter screening should be performed at the archetype level to systematically identify those simulation parameters with the biggest impact on simulation results. Kim et al [146] have proposed an alternative solution to the problem of unidentified uncertainties with the introduction of a non-specific unknown "life style" parameter to capture them, but its abstract character makes it, in the opinion of the author, difficult to use in future scenario analysis with the model. Finally, the potential relevance of the uncertainty intrinsic to simulation engines should be evaluated in each case, since it can be also responsible for part of the model error.

Regardless of the specific implementation, a new probabilistic modelling method for archetype parameters needs to be streamlined in UBEM, given the intrinsic lack of knowledge on the modeler's part about the diversity of the urban building stock. At a very minimum, all UBEMs should characterize occupant-related parameters through uniform uncertainty distributions, using reasonable minimum and maximum values based on available survey data and the modeler's expertise. Ideally however, such distributions should be calibrated by archetype and occupant type using the approach presented here or an equivalent technique. This of course requires the gathering of metered data samples by building type, and the development of UBEM models for their analysis. This task could be conducted by municipalities in collaboration with local utilities, which could maintain a calibrated database of archetypes available for modelers and designers, without violating any individual's privacy.

*4.4.2 Archetype sampling for validation*

The problem of calibration in UBEM has mainly been studied at the aggregate level, both spatial and temporal, due to the lack of validation data and large parameter uncertainties involved at the individual building level. However such an approach ignores the underlying diversity of demands, resulting in large errors when representing extreme loads. As a potential solution, the authors have proposed the archetype level as a more appropriate calibration scale. The proposed Bayesian approach has been shown to reduce errors in the 10 and 90 percentiles for a district EUI distribution to less than 15%. More importantly, it showed that a relatively small sample of 100 to 200 measured buildings from a particular archetype can be enough to calibrate key parameters, so it can be applied to other similar buildings in other districts. Parameter distributions obtained from Area 8 produced similarly low errors when applied to the Area 9/1 testing set. However, the results of this extended validation were not ideal, showing discrepancies in the demands of the oldest set of buildings, caused by sample variations between the two areas.

In this case study, the number of available measured buildings limited the sampling flexibility in calibration. Ideally, calibration should be performed separately by each archetype considered (Vintage, use type, occupant type, etc.), and sample sizes chosen so that the number of buildings per archetype is statistically significant. If the available sample of buildings by archetype is not large enough and the calibration of a model is performed in aggregation, the distribution of types within it should be equivalent to that of that archetype's general population. Although in this work Bayesian calibration was only validated against one second dataset, the confirmation of these sampling assumptions would require further analysis through repeated statistical bootstrapping of the overall available data set. Such an exercise would provide a distribution of error for multiple sample variations and scales of validation, and potentially identify an ideal sample size. Identifying a minimum sample size would be especially valuable for utilities, since it would provide an estimation of the effort and cost required for calibration.

### *4.4.3 Energy data resolution and accessibility*

The analysis of the UBEM model for AlQadisyah has shown the relevance of validating urban energy modeling techniques with measured energy demand data for individual buildings. However, the potential refinement of building archetype parameters through the proposed calibration approach would have been even higher if energy data had been available at a smaller temporal resolution. Unfortunately, privacy concerns make individual energy data still extremely difficult to access for large enough samples of buildings, especially in such small temporal scales. Hypothetical access to monthly measurements by building could characterize seasonal heating/cooling patterns in calibration, and increase the number of data points for error analysis resulting in a tighter calibrated joint distribution for the considered parameters. Furthermore, Bayesian calibration against building hourly energy data could inform the modeling of daily demand peaks, particularly relevant when considering alternative urban energy supply scenarios. In order to explore the performance of Bayesian archetype calibration in smaller temporal scales, and evaluate the additional effort level necessary, the following chapter of this dissertation (Chapter 5) will apply the methodology here introduced to a case study in Cambridge, MA.

In the opinion of the author, a strong collaboration is necessary between municipal governments and utilities to address these accessibility limitations. The method here proposed works towards facilitating this process, since with a limited sample of buildings it was shown to be possible to calibrate parameters for the complete population of an archetype. Therefore, general "archetype datasets" could be validated and made available by municipalities for further modeling with a reasonable effort level and without necessarily having access to metered demands for all buildings. Such somewhat "ideal" scenario would require a significant yet necessary effort to improve the current practices for documentation of the built environment. On one hand municipalities would have to establish a data collection infrastructure within their planning and building departments, capable of maintain archetype definitions, update them when new information is available, and validate parameter estimations with empirical surveys of buildings. On the other hand, local utilities and energy providers would have to define an acceptable data sharing workflow, which allowed modelers to access the required samples for validation.

## 4.5 Summary

This chapter introduced a new Bayesian-based approach to the calibration of archetypes, and applied it to the analysis of a residential UBEM in Kuwait City. The key contributions of the chapter are:

- Bayesian statistics can be applied in the calibration of UBEM models, in order to reduce the uncertainty of stochastic archetype parameters, especially those related to occupant behavior.
- Resulting archetype definitions can effectively reproduce measured distributions of building annual EUIs at the scale of the neighborhood, with errors lower than 5% in the mean EUI and 15% in the $10^{th}$ and $90^{th}$ percentiles of the distribution.
- Calibrated archetypes can achieve a 30-40% error reduction in the simulation of the $10^{th}$ and $90^{th}$ percentiles of the annual EUI distribution for a neighborhood, when compared to traditional uncalibrated deterministic approaches.
- The Bayesian calibration of an archetype based on a limited sample of 100-200 metered buildings can be sufficient to characterize the larger population it represents throughout a city, as long as occupant behavior and demographics in the building can be considered equivalent.

Chapter 5

# Archetype calibration to monthly energy data

The previous chapter introduced a Bayesian approach for the calibration of archetype-based UBEMs, and proved how it can be used to accurately reproduce annual energy demand distributions at the scale of a neighborhood. However, the analysis of urban energy strategies often requires the modeling of monthly seasonal and peak demands related to the use of heating and cooling. Using the residential building stock of Cambridge, MA as a case study, this chapter proposes and validates an extension of the method for the Bayesian calibration of archetypes, to the monthly, and potentially daily, temporal scale. In section 1, the problem is introduced and the chapter objectives are defined. In section 2, the case study is described in detail, and an error analysis framework for monthly calibration is introduced. Six modeling iterations of increasing detail are developed, including the annual and monthly calibration of six archetype parameters. Later, calibrated parameters are validated against a test dataset of 2,263 buildings belonging to the same archetype. Results are presented and discussed in sections 3 and 4.

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

*Sokol J, Cerezo Davila C, Reinhart CF (2016). Validation of a Bayesian-based method for defining archetypes in urban building energy models. Energy and Buildings 134, 11-24.*

## 5.1 Introduction

The validation in Chapter 4 of a calibration method for UBEM archetypes showed that it is possible to reproduce measured annual EUI distributions for a group of buildings, by using Bayesian statistics to update the uncertainty of select archetype parameters. Model uncertainty reduction was achieved using the error between simulated and real annual demands to estimate the likelihood of particular parameter combinations to be true. However, the energy consumption of a building is the result of a variety of factors (internal loads and occupancy, outside temperature changes, solar radiation, etc.) which are always a function of time. Some of them are seasonal in nature, and result in different heating and cooling loads depending on the month of study. Others influence energy demands on an hourly level, depending on the schedules of operation in the building or the position of the sun. Therefore, the calibration of archetype parameters based on errors analyzed at the aggregate annual level, while sufficient for the estimation of annual demands, cannot capture the impact of said parameters at monthly, daily or hourly levels, and might result in a misrepresentation of the real diversity of parameter values.

For many energy related urban strategies, especially those related to energy supply, distribution and storage, being able to reproduce such sub-yearly demands accurately is especially relevant. Hence, it is necessary to understand the viability of the proposed calibration framework in this context, and to adapt the methodology to accommodate the use of energy data with higher temporal resolutions. Adaptation challenges are very different depending on the scale considered. In the case of hourly or sub-hourly demands, building operation schedules (so far modeled deterministically) will have a very large impact in energy use, and would have to be treated parametrically as part of the model uncertainties. The stochastic modeling of hourly loads is a complex problem, extensively explored in research for the calibration of BEMs, and it is outside of the scope of this dissertation [135,138]. In the case of monthly loads, however, the variation of hourly schedules within a day will not have a decisive impact on the total demand, and the method can be extended. This chapter focuses on exploring this possibility, using as a case study the residential building stock of Cambridge, MA, for which monthly metered data for natural gas and electricity was made available by the local utility for the year 2008.

The general goal of the chapter is to understand the limitations of the proposed Bayesian calibration framework, when applied for the reproduction of monthly energy demands, with and without access to monthly metered demand data. To do so, two objectives are addressed in the following sections:

- To propose an expansion of the calibration method, in order to analyze simulation errors for multiple energy data points within a year.
- To evaluate the accuracy of the expansion in reproducing annual and monthly demands, and compare it with that achieved using uncalibrated or annually calibrated models.

## 5.2 Methodology

To explore the performance of Bayesian archetype calibration when monthly metered demands are available, a methodology is developed in the following sections, parallel in structure to that presented in Chapter 4. In this case, an UBEM is generated for a subsection of the residential building stock in Cambridge, MA, for the evaluation of archetype characterization methods. For the deterministic archetype definitions a combination of literature, building survey data and a statistical analysis of measured energy data was used to refine the uncalibrated archetype library. For the stochastic definitions a set of "uncertainty parameters" was picked based on both annual and monthly datasets. Table 5-1 provides an overview of the steps involved in the procedure. More detailed descriptions follow.

*Table 5-1: Workflow for the comparison and validation of characterization methods in Cambridge, MA*

| Analysis step | Methodology |
|---|---|
| 1 Urban data gathering | All available information for the selected district in Cambridge is gathered in collaboration with the local municipal government, including building geometry information, building properties and metered demand data. (Section 5.2.1) |
| 2 Archetype definition | Building archetypes are classified and characterized based on the available data, and energy data analysis, in three deterministic and 3 probabilistic iterations described in section 5.2.2. Characterization methods are summarized in Section 5.2.4, and uncertainty parameters are selected for calibration. |
| 3 UBEM model generation | A full urban building energy model is developed for both the training and validation datasets to be used in calibration. |
| 4 Archetype Bayesian calibration | Selected uncertain parameters are calibrated using the Bayesian approach (Chapter 4) based on a training set of buildings (399). The simulation of all parameter combinations is simplified with the generation of regression meta-models based on a coarse sampling of the parametric space. |
| 5 Energy demand simulation | Deterministic iterations are simulated using EnergyPlus, while stochastic cases are calculated based on the calibrated building meta models developed in step 4. |
| 6 Comparison and validation | Simulated EUI distributions for all iterations and compared against metered data for the training dataset buildings. Later, calibrated parameters are validated against metered data in the simulation of the validation dataset. |

### *5.2.1 Cambridge case study*

The residential building stock for the City of Cambridge, MA, was used as a case study for the application of the Bayesian calibration approach at a monthly temporal scale. Cambridge is deeply committed to the reduction of GHG emissions with a reduction target of 80% by 2050 [156] which it strives to meet through the improvement of its building stock. The city also formulated an ambitious Net Zero Energy Plan [157] with the intention of only permitting net-zero new buildings by 2030. The analysis in this chapter is limited to residential buildings with one to four units for which monthly metered demands could be obtained from the local utility. Other available data sources in Cambridge were similar in type and definition to those analyzed in Chapter 3, and they are listed below:

- *Building geometry:* Building shapes and heights were obtained from a GIS shapefile of buildings, released and updated regularly by the City of Cambridge [158].
- *Building data*: Descriptions of buildings located on every tax parcel were obtained from publicly available municipal property tax assessment records [159]. While these descriptions were solely developed for determining property taxes, they contain useful (if sometimes incorrect) information for energy modeling purposes, such as numbers of stories, room counts or fuels.
- *Measured energy consumption*: Electricity and gas meter readings were provided to MIT by the utility company EverSource (formerly NStar Energy & Gas), a supplier of electric and natural gas service in the Cambridge area [160]. Each meter had monthly readings spanning one or more months in the 2007-2010 year range. In the dataset, more meters had readings for all twelve months of 2008 than for any other year; hence, that year was selected for calibration.
- *Weather data*: An hourly weather file was created based on data recorded in 2008 by a local weather station [161] and supplemented by solar radiation data from Weather Analytics [162].

An extensive data analysis was developed on all available datasets, following the same procedures as already described for the Boston case study (Chapter 3) resulting in a complete and clean data set to derive an UBEM: The first data processing step was to link the tax assessment data to the tax parcel GIS shapefile and subsequently merge it with the buildings' GIS shapefile, thus associating building footprints and heights with their physical descriptions from the tax assessment. Additionally, energy data (reported by account numbers linked to addresses) was merged with tax assessment data (reported by tax parcel ID). Since each parcel could be associated with one or more gas and electric accounts, all meters for one address were summed to get the entire building's consumption.

It was not always clear whether all of a building's accounts had been included in the data provided, so the buildings whose number of accounts differed from the number of apartments reported in the tax assessment were excluded on the basis of incomplete data. Furthermore, only buildings that had seasonally-variable natural gas consumption – indicative of its use as the heating fuel – were retained, since the consumption of oil or other heating fuels was unavailable. While buildings without seasonal variation could be heated with electricity, they were not considered in the study in order to limit the analysis to one fuel combination type. Finally, EUI values for the years 2008 and 2009 were compared; buildings whose EUIs differed by more than 150% between these subsequent years were eliminated on assumption of incomplete data, non-standard behavior, or seasonal occupancy. The final subset of usable data contained 2,662 residential buildings across Cambridge (Figure 5-1). Of these, a subset of 399 located in the same neighborhood (Cambridgeport, highlighted in the figure) was used as the training set for calibration. The remaining 2,263 buildings acted as the testing set to validate the model.

*Figure 5-1: Metered and simulated buildings in Cambridge MA with highlighted training sample*

After pre-processing the data and merging it with building property data, energy consumption was normalized by floor area to calculate EUIs (kWh/m2). The following plots show histograms of the resulting annual EUI distributions for the building set (Figure 5-2), distinguishing between total and fuel based EUIs. The mean EUI found was 229 kWh/m2, with values ranging between 82 and 520 kWh/m2 (Table 5-2). The initial observations showed that the large majority of annual energy use is gas consumption for heating and hot water. Further analysis results are discussed in Section 5.4.

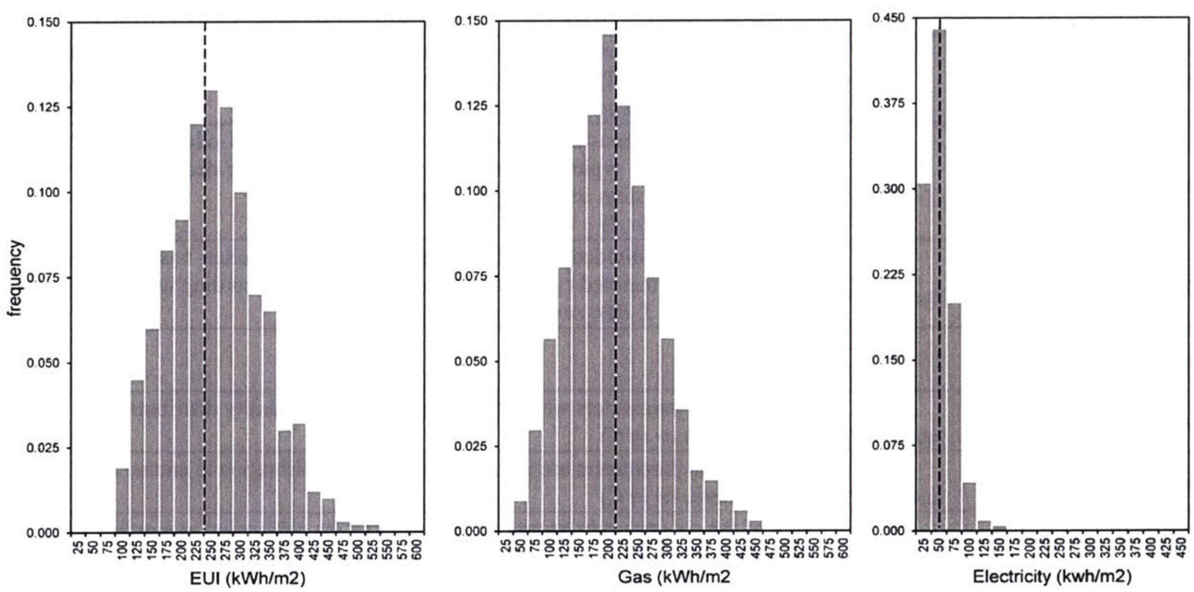



*Figure 5-2: EUI distributions for case study expressed as a total (a) and by fuel (b, c)*

*Table 5-2: Statistical values of annual EUI distributions for case study by fuel type*

| Fuel type | #Buildings | Mean (kWh/m2) | Std Dev (kWh/m2) | Minimum (kWh/m2) | Maximum (kWh/m2) |
|---|---|---|---|---|---|
| Total energy use | 2,662 | 229 | ±89 | 82 | 520 |
| Natural gas use | | 198 | ±53 | 83 | 366 |
| Electricity use | | 38 | ±20 | 6 | 142 |

### *5.2.2 Modeling iterations for monthly analysis*

In order to assess the effect of monthly energy data availability on UBEM calibration and accuracy, six iterations of increasing detail were defined for this study in a similar fashion to those defined in Chapter 4. These are labeled based on the information available to the modeler from the most general to the most specific (each iteration assumes information from the previous is available). The first two iterations (A-B) use deterministic archetype characterization based on available information. In addition to the two scenarios explored in Kuwait, a new level of definition was incorporated to the experiment (C): A scenario in which a modeler has access to monthly energy data, and can hence better classify buildings based on this information (see Section 5.2.3). The following three iterations (D-E-F) include both deterministic and probabilistic archetype parameters, with those chosen as uncertain focusing on occupant related variables. These are calibrated using both annual and monthly energy datasets. Table 5-3 summarizes the case study iterations and data sources used in each stage.

*Table 5-3: Modeling iterations by characterization method and data sources*

| Iteration | #Archs. | Archetype definition data sources |
|---|---|---|
| *Deterministic Parameters* | | |
| Literature (A) | 1 | Envelope constructions from Massachusetts Building Code 1980 [163]. Heating and cooling COPs from US DOE [164]. Internal loads and hot water consumption from US Residential Energy Consumption Survey (RECS) [90]. |
| Building Data (B) | 4<br>age | Envelope constructions from Massachusetts State Building Codes (1980, 1990, 2001) [163,165,166], and typical construction practices for earlier decades [118]. Presence of cooling A/C system according to taxes description.<br>*(Rest remains as in A)* |
| Energy Data (C) | 8<br>age, COP | HVAC systems divided into central air and central boiler based on multilinear regression from metered energy data, and characterized according to US DOE.<br>*(See Section 5.2.3, Rest remains as in B)* |
| *Stochastic Parameters* | | |
| Uncalibrated (D) | 8<br>age, COP | Six uncertain parameters were defined as uniform probability distributions.<br>*(Rest remains as in C)* |
| Annual Calibration (E) | 8<br>age, COP | Six uncertain parameters are updated via Bayesian calibration to annual data.<br>*(Rest remains as in C)* |
| Monthly Calibration (F) | 8<br>age, COP | Four of the six uncertain parameters are updated via calibration to monthly data.<br>(Rest remains as in C) |

*5.2.4 Archetype classification and characterization*

As described in Table 5-3, the number of archetypes considered to describe buildings in Cambridge was chosen according to the available data for each iteration case. For the most general iteration, based solely on literature (A), only one archetype was defined representative of all low-rise residences in the area. In iteration (B), the available building data in this case sourced from the Cambridge Tax assessment database, allowed for the further subdivision or archetypes by age of the structure into 4 vintages: Pre-1970, 1970 to 1980, 1980 to 1990, and Post-1990. Specifically, the Effective Year Built (EYB) tax metric, which indicates the year when the house underwent the last major retrofit, was the defining factor.

When energy data is available, it can be used to determine additional relevant classification variables. A multiple linear regression was performed for iteration C, using the building properties documented in the Tax dataset as explanatory variables, and the metered 2008 annual EUI as the dependent variable. Both $R^2$ and adjusted $R^2$ were used to understand the capabilities of tax parameters to explain EUIs. All non-categorical variables in the set, such as number of stories, bedrooms or chimneys were normalized by floor area. Strongly correlated variables were excluded (e.g. kitchens with bedrooms). Categorical variables included AC Use (No/Yes), Heating Type (Air/Water/Steam/Other), Foundation (NoSlab/Slab), Roof (Flat/Sloped), Building Type (Attached/Detached/SemiDetached), and Built Period. The analysis resulted in a value of 0.18 for both $R^2$ and adjusted $R^2$ values, and identified several significant tax variables for explaining the variance in EUI between buildings [167]. The low $R^2$ and adjusted $R^2$ values can be explained by the absence in tax records of key parameters influencing energy use, such as insulation levels or occupant behavior. In addition to age, already considered, the heating system type (gas boiler versus forced central air) was added as a classification indicator. Other significant variables in the regression analysis were either incorporated by default through the 3D geometry (e.g., detached versus semidetached home) or not included due to tool limitations. The resulting classification included 8 archetypes (4 ages x 2 heating systems), and was used through iterations D to F.

Characterization of deterministic parameters (A-B-C)

For the characterization of archetypes, each building and occupant model parameter needs to be assigned a value. In the Cambridge case study, envelope construction related parameters and system COPs were assigned deterministically by archetype in all six iterations. Table 5-4 lists the heat transfer values chosen in each case, derived from the sources described in Table 5-3, which included State Energy Codes by year, and the US DOE Reference Simulation Buildings used for Boston in Chapter 3. Window to wall ratios were assigned as average by period of construction. Remaining parameters, mostly related with occupant preferences, were defined deterministically in iterations A-B-C and stochastically afterwards, and are summarized in Table 5-5 again derived from sources in Table 5-3.

*Table 5-4: Summary of deterministic building parameters for iterations A-F*

| | | | Deterministic | | | Probabilistic |
|---|---|---|---|---|---|---|
| **Parameter** | **Units** | **Period** | **Literature** | **Building** | **Energy** | **All cases** |
| Wall U | W/m2K | Pre-1970 | 0.43 | 0.71 | 0.64 | 0.64 |
| | | 1970-1980 | | 0.52 | 0.55 | 0.55 |
| | | 1980-1990 | | 0.43 | 0.45 | 0.45 |
| | | Post-1990 | | 0.38 | 0.40 | 0.40 |
| Roof U | W/m2K | Pre-1970 | 0.28 | 0.62 | 0.56 | 0.56 |
| | | 1970-1980 | | 0.38 | 0.38 | 0.38 |
| | | 1980-1990 | | 0.28 | 0.28 | 0.28 |
| | | Post-1990 | | 0.15 | 0.20 | 0.20 |
| Slab U | W/m2K | Pre-1970 | 0.94 | 3.03 | 1.75 | 1.75 |
| | | 1970-1980 | | 1.32 | 1.03 | 1.03 |
| | | 1980-1990 | | 0.94 | 1.03 | 1.03 |
| | | Post-1990 | | 0.55 | 0.57 | 0.57 |
| Glazing U (SHGC) | W/m2K (-) | Pre-1970 | 2.72 (0.76) | 5.78 (0.82) | 3.12 (0.76) | 3.12 (0.76) |
| | | 1970-1980 | | 3.12 (0.76) | 2.72 (0.76) | 2.72 (0.76) |
| | | 1980-1990 | | 2.72 (0.76) | 2.72 (0.76) | 2.72 (0.76) |
| | | Post-1990 | | 1.96 (0.69) | 1.96 (0.69) | 1.96 (0.69) |
| Cool COP | - | Pre-1970 | 2.6 | 2.4 | 2.4 | 2.4 |
| | | 1970-1980 | | 2.4 | 2.4 | 2.4 |
| | | 1980-1990 | | 2.4 | 2.4 | 2.4 |
| | | Post-1990 | | 2.9 | 2.9 | 2.9 |
| Heat COP (Water/Air) | - | Pre-1970 | 0.80 | 0.80 | 0.75 / 0.85 | 0.75 / 0.85 |
| | | 1970-1980 | | 0.80 | 0.75 / 0.85 | 0.75 / 0.85 |
| | | 1980-1990 | | 0.80 | 0.75 / 0.85 | 0.75 / 0.85 |
| | | Post-1990 | | 0.80 | 0.75 / 0.85 | 0.75 / 0.85 |
| WWR | - | All | 0.15 | Average | Average | Average |

The additional classification insights obtained from buildings taxes and energy data influenced the characterization of parameters as well. In iteration B, the presence of air conditioning was defined according to the information reported by the tax auditors. In iteration D, some of the assumptions in previous iterations were revised in the analysis of metered monthly demands. The presence of air conditioning was inferred based on the ratio of electricity in the cooling season (July, August) to that in the shoulder months (May, October). Similarly, the peak flow for Domestic Hot Water was inferred by building (and not by archetype), based on the base load for natural gas in summer months. Finally, the COPs for the two main heating systems identified in classification were obtained from the ASHRAE Handbook of Fundamentals [168] and were assumed constant by period, since no evidence could be found about the likelihood of systems being upgraded through their lifetime.

Characterization of stochastic parameters (D-E-F)

In this case, six high-uncertainty variables were chosen by the author for the case study: Infiltration (INF), thermostat set points (HSET, CSET), occupant density (OCC), plug load and lighting power density combined (EQP), and the domestic hot water flow rate (DHW). Although the same limitations in the selection of model parameters described in Chapter 4 apply here, for the purposes of the study they were chosen based on the available information, the modeler's criteria, and a simple sensitivity analysis performed to the average building for each archetype. These parameters were initially characterized as uniform distributions with a minimum and a maximum acceptable value in iteration D, and later through calibrated joint distributions. In the case of EQP and DHW, metered data was used to inform the prior distribution in monthly calibration (F). Their values for all iterations are summarized in Table 5-5.

*Table 5-5: Summary of chosen uncertain parameters by iteration*

| | | **Deterministic** | **Probabilistic** | | |
|---|---|---|---|---|---|
| **Parameter** | **Units** | **All Cases** | **Uncalibrated** | **Annual Cal.** | **Monthly Cal.** |
| Occupancy (OCC) | occ/m2 | 0.021 | U(0.002,0.06) | Joint. Dist. | Joint. Dist. |
| Plug and Lighting (EQP) | W/m2 | 13.33 | U(2,40) / Data | Joint. Dist. | Joint. Dist. |
| Hot Water Peak Flow (DHW) | m3/h/m2 | 0.00015 | U(0.36,7.20)E-4 / Data | Joint. Dist. | Joint. Dist. |
| Cooling Set point (CSET) | °C | 25 | U(23,29) | Joint. Dist. | Joint. Dist. |
| Heating Set point (HSET) | °C | 20 | U(15,25) | Joint. Dist. | Joint. Dist. |
| Infiltration Rate (INF) | ach | 0.5/0.6/0.7/0.8 | U(0.1,1.5) | Joint. Dist. | Joint. Dist. |

As with the Kuwait model in chapter 4, hourly schedules associated with each one of these parameters in the model were defined deterministically, given the lack of hourly data, and their small impact in the aggregate demands over a month. For both the simulation and calibration of iterations D to F, the parametric space defined for the 6 parameters needed to be sampled so all relevant combinations were considered. Due to constraints of time and computing power, each distribution was divided into a discrete number of equally sized steps (3 to 5) resulting to over 1500 runs per building. To allow for finer sampling a regression statistical model was developed by building as described in the following section.

### *5.2.5 Monthly calibration methodology*

In order to apply the Bayesian method introduced in Chapter 4 for the calibration of parameters based on monthly energy data, it needs to be slightly modified. In the analysis of sub-yearly energy demands (Focus of this chapter) there is more than one data point available for comparison by building. Hence, in the error analysis step of the methodology acceptable limits need to be reformulated, to decide if a parameter combination vector is accepted or not. This can be done by either requiring that for all data points (In this case 12 months) the error between simulation and metered data stays within a limit, or by using a compound error metric. For the case of monthly calibration the author proposes to base the error limit ($\alpha$) on ASHRAE Guideline 14-2002 recommendations [110]. For calibration on an annual basis, the maximum percentage error (PE) was 5% of total energy per square meter (Equation 5-1). For calibration on a monthly basis, the allowable coefficient of variation of the root mean square error (CVRMSE) was set to 15%. The coefficient of variation is an addition of squared monthly errors, and serves as a measure of the monthly deviations from the observed pattern (Equation 5-2).

$$\text{PE} = \frac{EUI_{mes} - EUI_{sim}}{EUI_{mes}} \times 100\% \qquad (5\text{-}1)$$

$$\text{CV(RMSE)} = \sqrt{\frac{\Sigma(y_i - \hat{y}_i)^2}{(n-p)}} \times \frac{1}{\bar{y}} \times 100\% \qquad (5\text{-}2)$$

In this formulation of coefficient of variation, $y_i$ is the measured energy use for time interval $i$, $\hat{y}_i$ = the simulated energy use, $\bar{y}$= the mean of measured values, $n$ = the number of time intervals, and $p$ = 1 as the number of model parameters. All parameter vectors that resulted in allowable calibration errors, regardless of building, were combined into one posterior joint multivariate distribution for the district. A minimum 80% of explained buildings was required in order to accept the calibration. Results for updated parameter distributions for both annual and monthly calibration are described in Section 5.3.

As presented in chapter 4, the application of this Bayesian calibration method requires the simulation of all parameter combinations considered, to later identify those more likely to be true through error analysis. The use of 6 uncertain parameters with a fairly wide possible range of values (Section 5.2.4) hence results into a very high number of simulations per building (in the millions), unmanageable with normal computational resources. In this case, as presented before, the analysis steps per parameter were limited to 3-5, resulting in a coarse parametric grid. This problem limits the use of the proposed Bayesian calibration to small numbers of parameters and annual temporal scale, until faster UBEM simulation methods are proposed. To address this limitation, a combination of UBEM thermal simulation and statistical regression methods was used, in which a regression "meta-model" or ""surrogate model" is built for each building, based on the results of a small parametric space. In this case, using the results from the 1500 simulations by building, a polynomial function was obtained through linear regression, relating the six parameters' values to annual and monthly EUIs. The format of the polynomial function itself was adjusted by testing multiple configurations, fitting the seven function coefficients in each, and observing the resulting values for $R^2$ and $R^2$ adjusted as well as partial correlation plots for each parameter. In this case, coefficients were fitted using the least-squares method, as implemented through the function *lm()* in the R computational language [169]. The resulting numerical models had coefficients of determination higher to 0.90 (Table 5-6), and were considered suitable stand-ins for the much more time-intensive dynamic EnergyPlus simulations. While in this application, the very simplified surrogate model was sufficient to accurately represent the monthly energy use by building, any other building use or type at other temporal scales will require the further consideration of more complex regression techniques, extensively used in the optimization and calibration of full multi-zone energy models [170]. The surrogate model was then used to refine the parametric grid and include 12 to 20 steps per parameter. The same models were used to calculate annual and monthly EUIs in all three stochastic iterations D-E-F.

*Table 5-6: Regression meta-models' fit to EnergyPlus outputs.*

| **Dependent variables** | **Independent variables** | **# Models** | **$R^2$ mean (min, max)** |
|---|---|---|---|
| Annual EUI | INFIL, HSET, CSET, OCC, EQP, DHW | 399 (1 / bldg.) | 0.990 (0.984, 0.995) |
| Monthly EUI | INFIL, HSET, CSET, OCC, EQP, DHW | 4788 (12 / bldg.) | 0.979 (0.937, 0.991) |

### *5.2.6 Model simulation and evaluation*

Full UBEMs were generated by iteration case, for the comparison of simulation and metered demands. The multi-tool workflow introduced in Chapters 3 and 4 was used for that purpose, using the Cambridge GIS shapefile as a base input for building geometry, which was then extruded according to the reported height. Multi-zone energy models for all buildings as well as 3D context shading were generated within Rhino 3D [70] and Grasshopper [123], while archetype parameters were assigned through a JSON template library file [51]. Archetype data was associated with each building within Grasshopper, and used to generate individual energy models using Archsim [52]. All simulations were developed using EnergyPlus [16], and the processing of result errors was performed within the R language [169].

Regarding the sampling of parameters in iterations E and F, a Markov Chain Monte Carlo (MCMC) algorithm was applied in this case. The use of a "statistical" surrogate model allowed obtaining a number of EUI results sufficient to represent the complete parametric space (Section 5.2.5), while maintaining a reasonable computation time. Using this procedure, each building was sampled 1000 times, resulting in 339,000 energy results for the training dataset in Cambridgeport, and 2,263,000 results for the testing set. However, the use of approximate surrogate models for each building is potentially introducing additional errors in the model which need to be explored in more detail in the future. The results by model iteration (Table 5-1) for the training dataset buildings (399 models) were evaluated, using the same metrics of annual percentage error (PE) and monthly coefficient of variation applied in calibration. These two metrics were calculated for every building in the set individually. The distributions of simulated energy use intensities (EUIs) of all buildings were compared to the measured distributions with both metrics on the basis of the mean ($\mu$), standard deviation ($\sigma$), and the KS statistic ($D_n$), as described in Chapter 4. For model validation, the archetypes with calibrated parameter distributions derived from the original 399-building training set were applied to a set of 2,263 similar residences in Cambridge.

## 5.3 Results

The implementation of the previously described methodology resulted in over 300,000 EnergyPlus simulations for the calibration of parameters, plus over 2,500,000 sample runs of the "meta-model" developed in the analysis of cases D to F. The results from all iterations for the training dataset buildings are described in detail in the following sections. Later, simulations based calibrated parameter distributions are validated against measured energy use for a comparable but different set of buildings in Cambridge.

### *5.3.1 Analysis of available energy data*

The initial exploratory analysis of the measured energy dataset, focused on identifying building characteristics that may help in their classification into archetypes. Multivariate linear regression of the building properties in the tax assessment data to annual energy data identified several variables as significant in explaining the variance in EUI between buildings, as described in section 5.2.4. EUIs were more correlated with a building's Estimated Year Built (EYB), i.e., the age of the latest building renovation, than with its original construction date or Actual Year Built (AYB), so the EYB was used for archetype classification. For newer buildings with no EYB available, AYB was used instead in the analysis. In addition to age, other significant variables included the heating system type (boiler versus forced air), purely geometric categories that were incorporated by default in the UBEM 3D model (e.g. detached versus semidetached, number of stories), and some others more than were not included due to tool limitations (e.g. fireplaces, shape of roof). Heating system type, with a value of $p < 0.01$ and a significant correlation coefficient, was chosen as an archetype classification indicator.

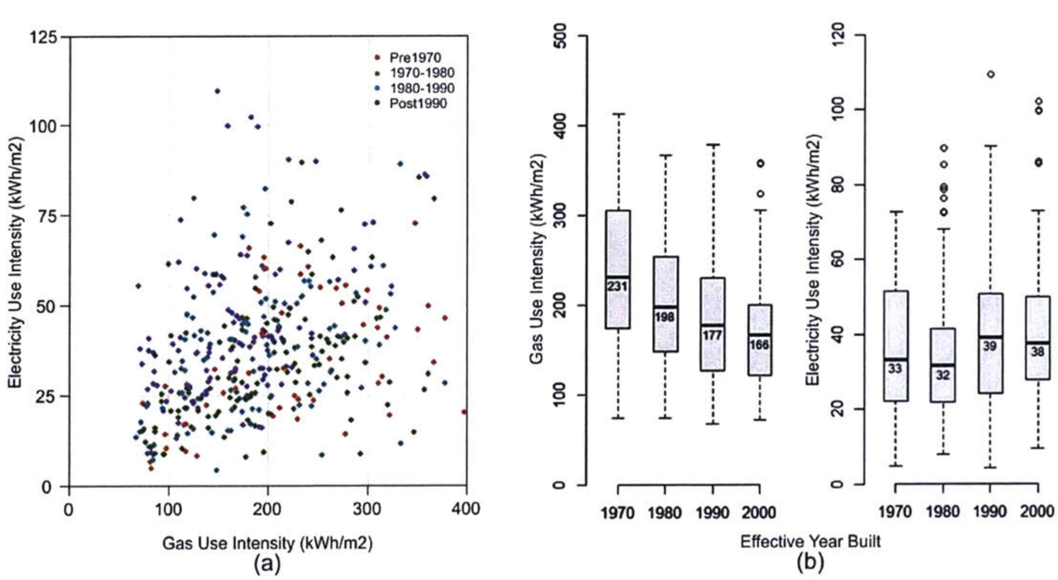



*Figure 5-3: (a) Measured electricity EUI plotted against gas and (b) EUI Boxplots of gas (left) and electricity (right) EUIs*

To understand the trends in energy use in the sample, the metered data was further analyzed by fuel type, i.e. gas and electricity. Figure 5-3a shows a weak positive correlation between measured annual use intensity of electricity versus natural gas for all buildings in the sample. More trends are visible when the set is divided by building age in Figure 5-3b. The boxplot shows a downward trend in both the average gas consumption and its variance within each group as the building's renovation date increases. For electricity use, however, newer buildings have slightly higher average consumption. As newer buildings have better air-sealing and insulation due to increasingly stringent code requirements, the downward trend in gas, used largely for heating, is plausible and confirms the archetype classification. The narrower distribution of gas EUIs for newer buildings can be a result of higher construction standards and quality control. When considering electricity use, the lack of a clear age-based trend points towards a larger influence of plug and lighting loads, and justifies their introduction as uncertainties in iterations D-E-F.

### *5.3.2 Effect of energy data availability on parameter distributions*

The effects of the two levels of calibration, annual and monthly, on the posterior parameter distributions were compared as well. Distributions for the six probabilistic parameters are shown in Figure 5-4. Prior distributions are plotted for reference as red lines. For the monthly iteration (F), in blue in the graph, the first four parameters (HSET, CSET, INF, OCC) are the direct result of calibration. The distributions of the last two parameters (EQP, DHW) were derived in calibration for each building based on its monthly electricity and gas base loads (See Table 5-5).

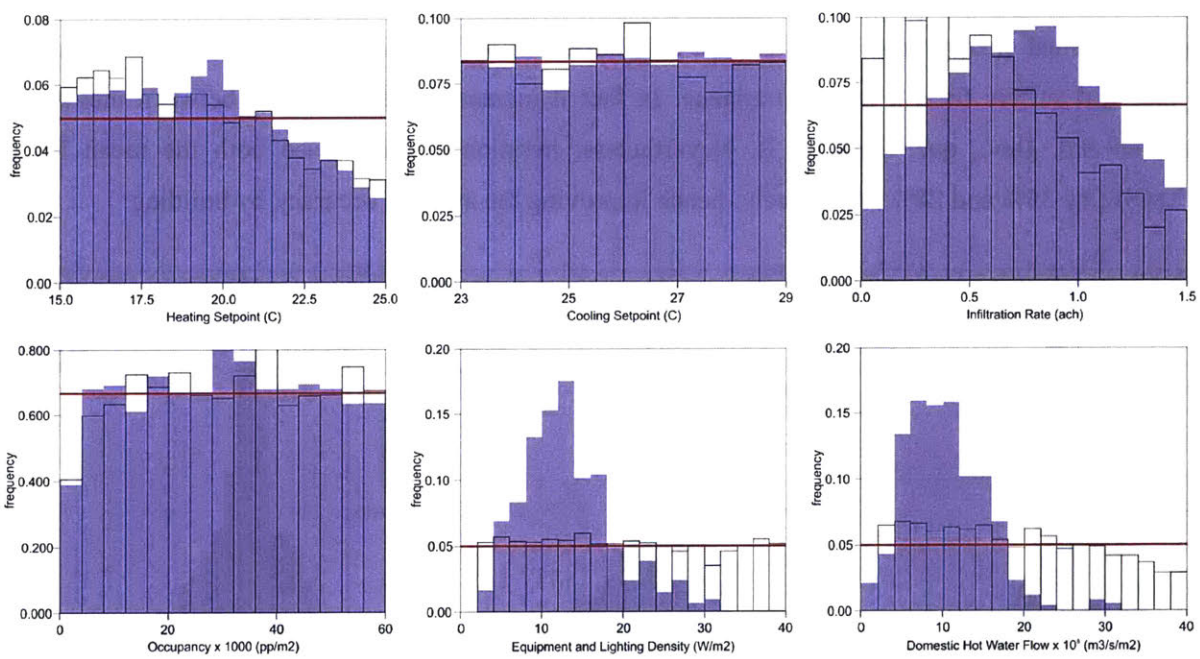



*Figure 5-4: Prior (red line) and marginal parameter distributions in annual (white fill) and monthly (blue fill) calibration*

First, the plots show relevant differences between annual and uncalibrated distributions mostly in 3 parameters (heating set point, infiltration, and domestic hot water) while the others deviate minimal from their uniform priors. Second, a very clear variation can be observed between the posteriors resulting from annual or monthly calibration in the cases of heating set point, infiltration, hot water and equipment loads, due to the different methods for the calculation of errors. The additional constraints imposed by the monthly error should presumably result in more realistic distributions. This difference is especially visible in the last two parameters, equipment and hot water, since in the monthly analysis case their prior distributions were obtained directly from the metered data. At the end of the process, the posteriors of two parameters, occupancy and cooling set point, did not depart far from their initial uniforms, showing a smaller effect on the general energy use of the buildings.

*5.3.3 Model accuracy by modeling iterations*

The first three iterations of the 399 buildings training set (A-B-C), which relied on deterministic archetypes, were analyzed first. The distributions of modeled against measured EUIs for all buildings are plotted in Figure 5-5, and their quantitative comparison is presented in Table 5-7. As with the case of Kuwait in Chapter 4, the first two iterations, created with one and four archetypes respectively, resulted in narrow EUI distributions which overestimate the mean and do not capture the real variance. Iteration "Building Data" (B) improved over "Literature" (A), confirming that the use of EYB in defining archetypes did aid in reflecting EUI differences. The third iteration, which increased the number of archetypes to eight, and in which envelope constructions were adjusted on the basis of regression to measured annual energy usage, resulted in a distribution with almost identical mean to the metered one but that still suffers from a narrow variance. In fact it increased the difference between metered and simulated Std. Dev., over iteration B. Nevertheless, iteration C did reduce both the mean PE and CVRMSE, by 35% and 20% respectively, hence improving the average accuracy by building.

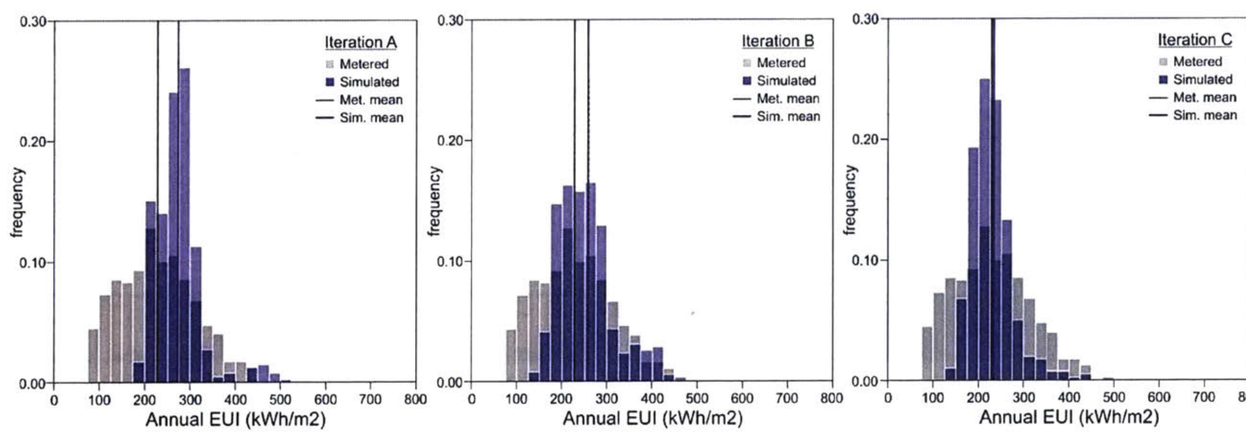



*Figure 5-5: Metered and simulated annual EUI histograms for training set (n = 399) for iterations A-B-C*

*Table 5-7: Error metrics summary for the training set in for iterations A-B-C*

| Metric | Units | Metered | Literature (A) | Building Data (B) | Energy Data (C) |
|---|---|---|---|---|---|
| EUI Mean<br>Std Dev | $kWh/m^2$ | 229<br>±83 | 273<br>±51 | 258<br>±72 | 228<br>±47 |
| Mean PE | % | -- | 47.1 | 27.7 | 12.3 |
| Mean CVRMSE | % | -- | 64.6 | 60.4 | 45.2 |
| KS Statistic | -- | -- | 0.39 | 0.24 | 0.22 |

Next, the model was run with the six uncertain parameters sampled from their prior distributions in iteration D. In iterations E and F, these distributions underwent two Bayesian calibration procedures using known energy data at annual and monthly scale as outlined in Section 5.2.5. Errors were calculated using Equations (5-1) and (5-2). In the process of calibration, a building was labeled *explained* if there was at least one parameter vector that resulted in an acceptable calibration error, and *unexplained* otherwise. Thus, the label *unexplained* implies that no combination of parameters was able to generate an output close to the measured energy consumption. Unexplained buildings could be a consequence of: (1) the building exhibiting unusual behavior in its metered energy; (2) simplifications used in the energy modeling process; (3) overly narrow ranges for the probabilistic parameters and/or incorrect assumptions for the non-variable parameters. Using a calibration error based on *monthly* energy resulted in 16.5% of the buildings being unexplained, compared to 0.03% when using annual error (Table 5-8).

*Table 5-8: Summary of the calibration metrics and results*

| Calibration | Error metric | Max error | #Explained Bldgs. | #Unexplained Bldgs. |
|---|---|---|---|---|
| Annual | PE | 5% | 398 (99.7%) | 1 (0.03%) |
| Monthly | CVRMSE | 15% | 333 (83.5%) | 66 (16.5%) |

Figure 5-6 shows the histograms of measured versus simulated annual EUIs with uncertain parameters sampled from prior distributions before calibration (D), posterior distributions after annual calibration (E), and posterior distributions after monthly calibration (F). Samples from the prior distributions resulted in a EUI spread significantly wider and with a higher average than measured, indicating the shortcomings of using uncalibrated parameter distributions. Both plots with posterior parameter distributions showed a clear advantage over the uncalibrated one, with errors below 15% in both the mean and Std. Dev. of the EUI distribution. The two calibrated plots were comparable at the annual EUI level for most of the error metrics. Between the two, monthly calibration (F) achieved better results in all cases, especially for the KS statistic (Table 5-9). However, mean PE and CVRMSE values were almost equal to those on deterministic iteration C, showing that calibration achieves better results at the scale of the set, but cannot estimate the correct parameters for an individual building.

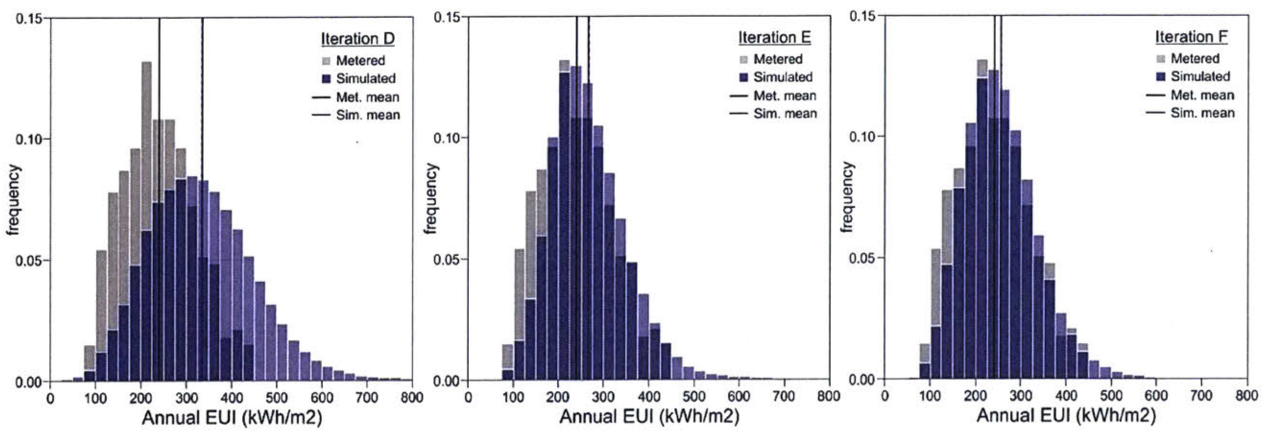



*Figure 5-6: Metered and simulated annual EUI histograms for training set (n = 399) for iterations D-E-F*

*Table 5-9: Error metrics summary for the training set in for iterations D-E-F*

| Metric | Units | Metered | Uncalibrated (D) | Annual (E) | Monthly (F) |
|---|---|---|---|---|---|
| EUI Mean<br>Std Dev | kWh/m$^2$ | 237<br>±79 | 334<br>±118 | 270<br>±89 | 258<br>±83 |
| Mean PE | % | -- | 54.8 | 25.5 | 19.4 |
| Mena CVRMSE | % | -- | 82.0 | 58.9 | 54.2 |
| KS Statistic | -- | -- | 0.38 | 0.18 | 0.09 |

The greater accuracy provided by monthly calibration (F) was revealed when looking at the monthly distributions separated by fuel (Figure 5-7). January and July were chosen for comparison, as they featured the largest contrast in gas and electricity use. The annually-calibrated model (E) did not show good agreement to measured data when compared at a monthly level with electricity and natural gas considered separately (left side of the figure). Most noticeable was the mismatch in electric use, with simulated results showing relatively uniform frequencies across the range 0-11 kWh/m$^2$, while measured data had a pronounced peak at 3-4 kWh/m$^2$. On the other hand, the model with monthly calibration showed a better fit, accounting for both seasonal differences and the non-uniformity of electric loads.

*Table 5-10: Error metrics summary by month for iterations E-F*

| Metric | Units | Month | Metered | Annual (E) | Monthly (F) |
|---|---|---|---|---|---|
| EUI Mean μ (Gas/Elec) | kWh/m$^2$ | January | 30.0 / 4.5 | 39.0 / 5.5 | 34.0 / 3.8 |
| | | July | 3.3 / 3.2 | 8.0 / 5.7 | 3.5 / 3.3 |
| Std Dev σ (Gas/Elec) | kWh/m$^2$ | January | ±5.0 / ±1.5 | ±16.0 / ±3.5 | ±10.0 / ±1.4 |
| | | July | ±0.8 / ±0.4 | ±5.5 / ±3.7 | ±1.0 / ±0.5 |
| PE (μ) (Gas/Elec) | % | January | -- | 30.0 / 22.0 | 14.6 / 15.0 |
| | | July | -- | 142.3 / 78.1 | 6.0 / 3.0 |
| PE (σ) (Gas/Elec) | % | January | -- | 220.0 / 133.3 | 50.0 / 6.6 |
| | | July | -- | 587.5 / 825.0 | 25.0 / 22.5 |

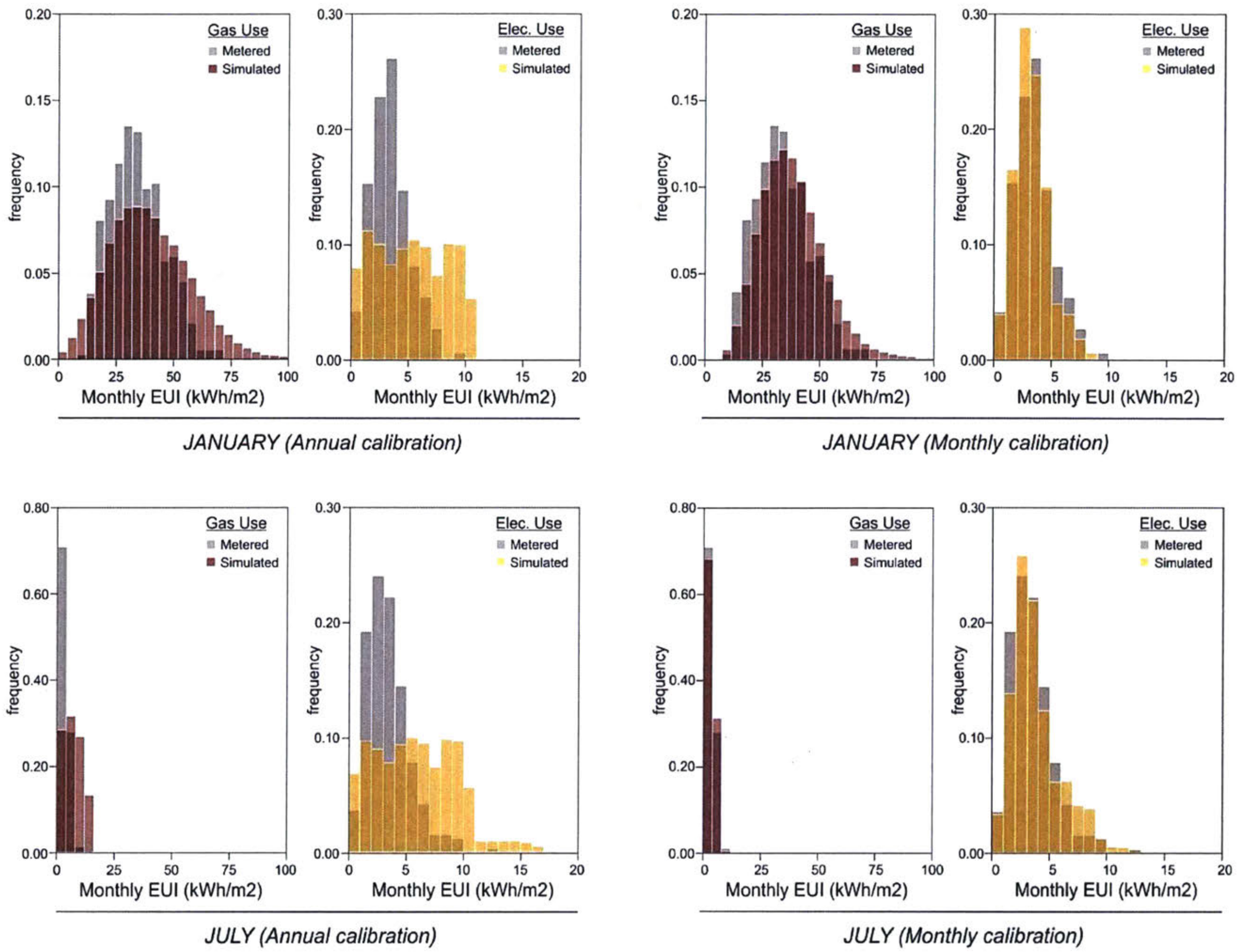



*Figure 5-7: Metered and simulated EUIs from annual and monthly calibration (E-F), for January and July by fuel type.*

The error in both gas and electricity for mean consumption was reduced below 15% in January and July after the monthly calibration. The errors for the standard deviation, while still relevant, were reduced by more than a 100% from annual to monthly calibration. Results showed that the addition of probabilistic parameters to archetypes results in a more realistic spread of EUIs than fully-deterministic definitions by allowing the model to account for diversity of occupant behavior within buildings of the same type. However, it does not necessarily result in a better-fitting model unless these distributions undergo calibration. Calibration based on a monthly error metric (CVRMSE) improves upon annual if sub-annual energy consumption is of interest.

### *5.3.4 Model validation after calibration*

While the proposed methodology resulted in a better-fitting model as described above, the parameter distributions used in these models were derived directly from measured energy data for the set of buildings being modeled. Therefore, a validation exercise similar to that applied in Kuwait in Chapter 4 was done to determine whether the calibrated parameter distributions would apply to other areas.

With this aim, another 2,263 low-rise residential buildings in Cambridge were used as the validation set. Parameter samples were taken from the distributions calibrated using the original training set, as described in Section 5.2. Figure 5-10 and Table 5-11 present the results in iterations D-E-F for the validation set. As before, there was an improvement in model fit for each subsequent iteration. Notably, Figure 5-10 demonstrate that expressing high-uncertainty parameters probabilistically greatly improved the model, even when those distributions were calibrated to data for a different, smaller set of buildings. The error in the mean and standard deviation was again smaller in the monthly case and below 15% when compared to the metered data. The mean PE and CVMRSE had values between 40 and 60%, as with the training set, pointing to the same conclusions as in that case. In addition, the monthly gas and electricity EUIs obtained in iteration F presented equivalently low errors (below 15% in the mean and average for January and July) to those described in the previous section.

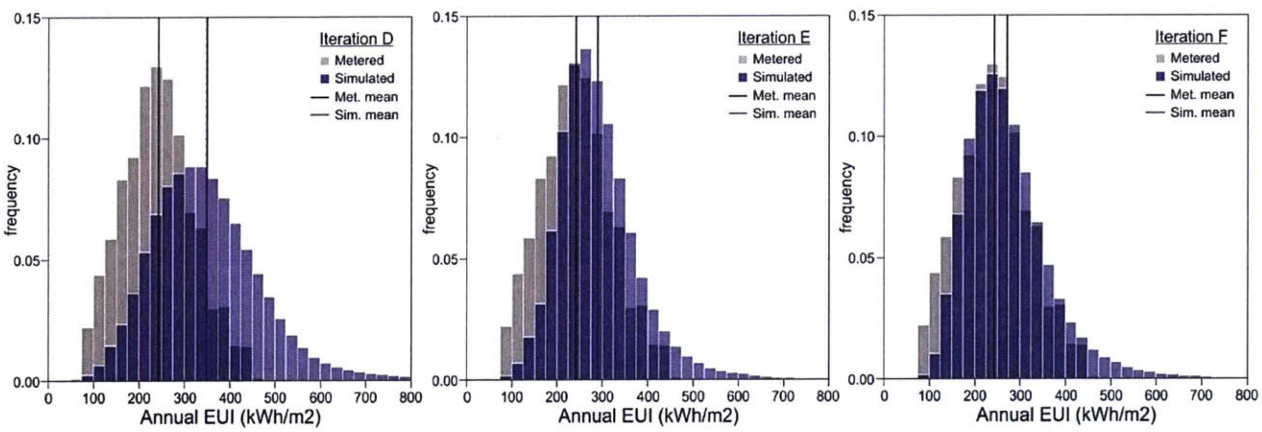



*Figure 5-10: Metered and simulated annual EUI histograms for validation set (n = 2,263) for iterations D-E-F*

*Table 5-11: Error metrics summary for the validation set*

| Metric | Units | Metered | Uncalibrated | Annual | Monthly |
|---|---|---|---|---|---|
| EUI Mean<br>Std Dev | kWh/m$^2$ | 242<br>±78 | 349<br>±120 | 289<br>±92 | 272<br>±87 |
| Mean PE | % | -- | 69 | 47 | 44 |
| Mean CVRMSE | % | -- | 87 | 66 | 58 |
| KS Statistic | -- | -- | 0.41 | 0.21 | 0.10 |

## 5.4 Discussion

Based on the previously described results, this section draws conclusions about the effectiveness of the proposed calibration method depending on the temporal scale of available energy data. In addition, the potential application of statistical regression building meta-models for reducing simulation and calibration times is discussed in the context of large UBEM models, especially at sub-yearly temporal scales.

### *5.4.1 Annual vs monthly calibration data*

The work developed in this chapter has explored the additional level of detail in the characterization of archetypes, which can be achieved when monthly demand data by fuel is available. The author compared the accuracy of an UBEM model resulting from the use of deterministic and stochastic uncalibrated parameters, as well as parameters calibrated using both annual and monthly data. The access to monthly data was proven valuable for any modeling technique, by using it to identify the presence of air conditioning or electric heating in buildings, later applied as an indicator for archetype classification. More importantly, it was used to estimate key archetype parameters in order to successfully calibrate an UBEM at the monthly scale. To do so an extension to the calibration method was introduced, with the addition of a compound error metric (CVRMSE) to calculate the difference between monthly simulated and metered demands.

The accuracy improvement from the use of parameters calibrated to monthly instead of yearly measurements was minor when viewed on an annual basis (a decrease from 13.9% to 8.9% for the error in the EUI mean). However, a very significant improvement was observed when comparing the two calibration scales by month, since the annually calibrated parameters were completely unable to reproduce correctly the distribution of gas and electricity consumption in winter or summer. This result leads to two main conclusions: First, that that calibration with higher frequency data is necessary if modeling seasonal variations is relevant for the modeling purpose (e.g. for estimating varying energy demands throughout the year or for modeling weather-dependent retrofit options). Second and more relevant, that an UBEM should only be expected to perform accurately to the temporal level it has been calibrated. While relatively evident, this point is, in the opinion of the author, a powerful argument in favor of making high frequency demand data more accessible. Current mandatory or voluntary disclosure programs such as BERDO in Boston [9] only require utilities or real estate owner to report annual demands, with almost no complementary information about fuels, end uses or characteristic of the buildings. For UBEMs to become effective for the analysis of supply scenarios, this has to change.

An additional consequence of using higher-frequency data for calibration is that fewer buildings end up meeting the calibration error requirements, i.e. are not explained properly by the model. In the case study, 16.5% of the buildings were not explained when calibrating to monthly data (compared to less than 1% unexplained when using annual data). This is a necessary consequence of increasing the number of data points evaluated, and can give additional insights to the modeler, since either these buildings behave completely outside of the normal range for residential structures, or the archetypes and parameters chosen are unable to account for all variations. The unexplained buildings can be flagged for further examination or potentially marked as priority targets for energy efficiency measures.

Finally, it is important to discuss the changes in parameter distributions resulting from calibrating to monthly instead of annual data. The difference is explained by the fact that none of them is necessarily representing the distribution of the parameters in the specific buildings considered. Instead they are capturing all uncertainties in the model at the aggregate scale of the archetype, and as discussed before, should not be applied for the modeling of individual buildings. The further development of the methodology will require the comparison of the obtained posterior distributions, with empirically monitored data from a similar sample of buildings, which is unfortunately very difficult to obtain.

*5.4.2 Hybrid modeling with statistical methods*

In addition to incorporating monthly energy data in calibration, this chapter revealed some of the computational limitations of the propose calibration framework. The method requires the simulation of a very large parametric space in order to later identify those parameter combinations more likely to be true in the model. Furthermore, once calibrated, the later sampling of the joint parameter distribution for the simulation of any analysis scenario requires equally large numbers of EnergyPlus simulations. As the number of buildings and parameters considered increases, the required time and computational power easily becomes unmanageable, at least with current computers and simulation engines. In this case the calibration of almost 400 buildings with 6 parameters required hundreds of thousands of runs with a fairly coarse discretization of the parametric space. For that reason, the author tested the combination of UBEM thermal modeling with statistical modeling techniques, for a hybrid solution in which only a few parameter combinations were calculated in EnergyPlus. Later, energy demands in parameter combinations, that were not initially considered, were estimated using simple linear meta-models to substitute the costly EnergyPlus simulations. It is the opinion of the author that this hybrid thermal/statistical modeling approach is a necessary step during the further calibration of urban models.

The use of regression meta-models, or surrogate models, has been explored in research for the calibration of BEMs but is not the only statistical modeling application which could help reducing calibration and simulation times of stochastic UBEMs. In further research, advanced sampling techniques could be studied to calculate the minimum number of buildings necessary to reduce archetype uncertainty to acceptable levels. Similarly, as already discussed in chapter 4, sensitivity and screening techniques could be used to minimize the number of relevant parameters. If the modeler can have access to larger energy data samples or the option to choose specific buildings, calibration could also be streamlined and improved through better experiment design methods (DOE). For example, blocking techniques could be applied in calibration by isolating buildings with the same occupancy, or factorial experiments could be used to better understand the potential interaction between parameters. Lastly, spatial clustering techniques for the simplification of thermal models, such as the "shoeboxer" approach [22], can also reduce simulation times by identifying similar geometries within the built environment. In parallel to the consideration of statistical methods, the growing availability of online parallel "cloud" computing services and the use of Graphic Processing Units (GPUs) will also contribute to overcoming these limitations in the future.

## 5.5 Summary

This chapter proposed an extension for the previously introduced Bayesian archetype calibration method, for its use with monthly metered energy data. The UBEM method was tested and validated in the analysis of a sample of 2,662 buildings in Cambridge, MA. The key findings of the chapter are:

- Bayesian archetype calibration techniques are only effective for the accurate reproduction of energy demands at the temporal scale for which metered data is available.
- The application of Bayesian calibration when monthly demands are available for a sample of buildings requires the definition of a compound error metric. The CVRMSE, as described in ASHRAE Guideline 14-2002 for the calibration of BEMs is a viable error metric for that purpose as shown in the analysis of a residential case study in Cambridge, MA.
- Resulting archetype definitions effectively reproduced measured distributions of building monthly EUIs at the scale of the district, with errors lower than 5% in the mean EUI and 15% in the standard deviation of EUIs.
- The study of a larger number of calibration parameters (in this case 6) and/or a larger number of building samples can significantly increase simulation time, to the point of making UBEM calibration unpractical with current computational power. This chapter has shown how statistical regression meta-models can be used in combination with UBEM to facilitate the simulation of larger parametric spaces in a limited timeframe.

Chapter 6

# Applications in energy policy and design

Previous chapters made a case for archetype-based UBEMs, and proposed and demonstrated a calibration method for stochastically defining archetypes. However, the significant amount of time and effort required in the generation of calibrated UBEMs can only be justified if the models can afterwards provide valuable insights for urban decision makers, which would have not been available based on simpler, static UBEMs. This chapter explores the applicability of a calibrated archetype-based UBEM to provide actionable information to policy makers, local utilities and urban designers. In sections 1 and 2, the main stakeholders involved in planning the energy ecosystem of a city are introduced, and a schematic model for collaboration is proposed that would enable in practice the use and maintenance of a municipal UBEM. Two application cases are introduced for the evaluation of energy efficiency policies in a Kuwaiti neighborhood, and the analysis of an urban design proposal in Boston. Energy models are created and simulated for both cases, and their results are discussed in section 3 and 4 from the perspectives of different relevant decision makers.

*Elements of this chapter have been published in the proceeding of BS2017:*

*Cerezo Davila C, Jones N, AlMumin A, Hajiah A, Reinhart CF (2017). Implementation of a calibrated Urban Building Energy Model (UBEM) for the evaluation of energy efficiency scenarios in a Kuwaiti residential neighborhood. 15th International Conference of IBPSA, 7-9 August 2017, San Francisco, CA.*

## 6.1 Introduction

So far, the work presented in this dissertation has concentrated on developing a collection of methods for generating UBEMs of the existing city. For that purpose, the author has demonstrated that it is currently possible to build a static citywide model based on widely available data sets, and that, with additional access to metered energy samples it is further possible to calibrate the underlying archetypes to represent urban energy demands with acceptable accuracy. All of these contributions rely on the assumption that an UBEM can become an effective energy planning tool for municipalities. In fact, throughout the existing literature, bottom-up urban energy models have been proposed as a supporting instrument for a variety of urban applications, including GIS energy mapping [98,171], emissions calculation [172], fuel poverty policy [20], supply systems design [21], and evaluation of master planning competitions [173]. Ultimately the purpose of an UBEM is to compare future energy scenarios with existing conditions in the built environment, and quantify their impacts in terms of demands, emissions, costs or resilience. As a direct example of the use of an UBEM in ongoing planning efforts in Boston, researchers at MIT Lincoln Lab used the synthetic building loads generated in Chapter 3 to identify potential locations for Combined Heat Power plants and micro grids (Figure 6-1). To do so, the team mapped hourly demands for electricity and heating around high usage building clusters and optimized system sizes for cost and emissions, distinguishing between more so-called multiuser energy justice and emergency micro grids [174]. The resulting map has been made public by the Boston BPDA and can be accessed online [175].

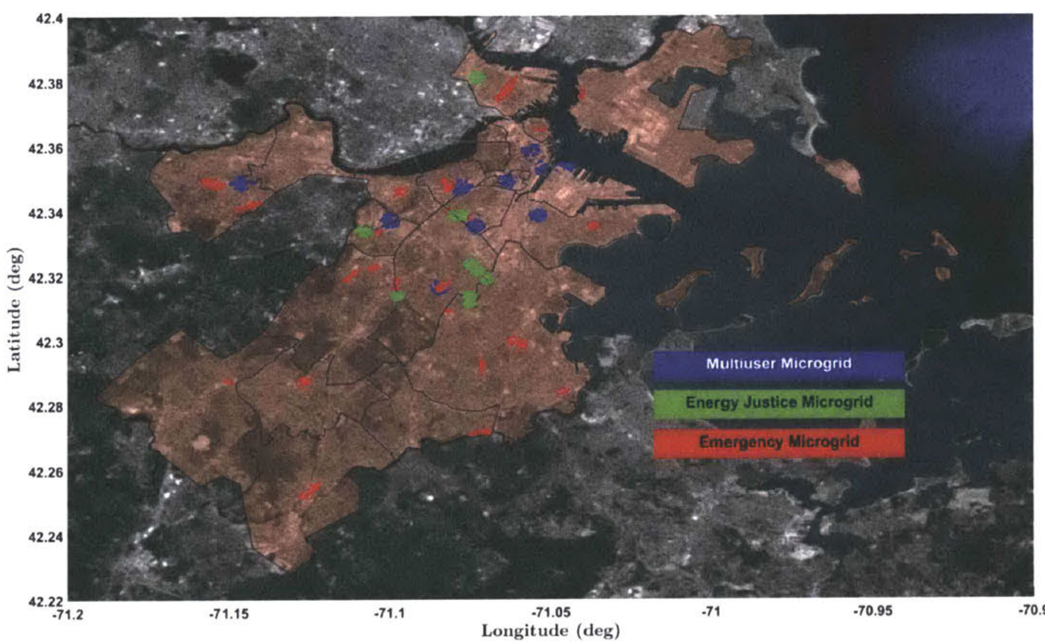



*Figure 6-1: Selected micro grid locations in Boston based on citywide UBEM results (MIT LL 2016)*

All such applications require a degree of calibration, because if a model cannot accurately reproduce current energy demands at the scale of the analysis, its results about future interventions might mislead a decision maker. While the techniques proposed in previous chapters offer partial if not complete solutions to this issue, they also depend on the collaboration of utilities and owners to provide energy data, and, as of today, they require a non-trivial investment of modeling time and resources. To justify these efforts, the resulting UBEMs need to provide actionable information to decision makers, which they would not get from an uncalibrated model. Hence, we have to understand in which modeling scenarios the calibration of stochastic archetypes as described in Chapters 4 and 5 is relevant and necessary. The general goal of this chapter is hence to address the "Application" hypothesis presented in the introduction, and demonstrate how a municipal, calibrated UBEM can be used to inform energy related strategies. To do so, three objectives are addressed in the following sections:

- To define general requirements of a collaboration framework for the development and maintenance of a municipal UBEM.
- To compare the usefulness of deterministic vs stochastic calibrated UBEMs for the analysis of future policy and design scenarios.
- To explore examples of their potential application from the different perspectives of municipal employees, local utilities and urban designers.

## 6.2 Methodology

To address these goals regarding the relevance of calibrated UBEMs, an implementation study is developed in this chapter, structured in two main sections. First, potential stakeholders in the urban energy planning space are identified. Based on them, the author discusses the collaboration framework necessary for the implementation of UBEM techniques in a city. Second, two application cases are developed based on the research results for Kuwait and Boston. In each case, one energy-related strategy is analyzed in simulation, using both deterministic and calibrated archetype parameters. The two application case studies are summarized below, and described in detail in the following sections.

1 <u>Energy demand policy (Kuwait):</u> The district UBEM calibrated for AlQadisyah in Chapter 4, is applied to estimate energy demand savings for three building retrofit and two electricity pricing scenarios. Differences between deterministic and stochastic archetypes are discussed.

2 <u>Urban design compliance (Boston):</u> Calibrated occupant parameters for Cambridge residences in Chapter 5, are applied in the comparison of two urban design proposals in the Boston Seaport District, in terms of energy use and performance certification.

*6.2.1 Stakeholder perspectives and application framework*

As with any other aspect of urban policy, building energy issues affect a large number of institutions and individuals. On the one hand, these include public or private entities in charge of the planning and management of power generation and supply. On the other end, there are building owners and users responsible for operation and demands. Municipalities sit somewhere in between these two groups and have to regulate to a certain extent the built environment to achieve their environmental, economic and safety energy-related goals. Only some on the energy "stakeholders" are involved in making decisions regarding buildings and would benefit from access to a calibrated UBEM. Main stakeholder perspectives relevant for this discussion are described in the following using Boston as an example:

1 Municipal policy makers: Public officials in charge of developing and implementing the long term energy and emission goals for the city as a whole. In Boston this work is performed by the Environment, Energy and Open Space Department, as well as by members from the Mayor's Office. Since the work developed by these departments necessarily engages the energy ecosystem in multiple levels, they would be the main beneficiaries of a municipal UBEM. Its potential applications can be grouped around demand and supply:
   - *Demand applications*: Definition of energy use baselines for new construction or building retrofit programs; citywide energy and emissions accounting and mapping; evaluation and implementation of energy efficiency strategies (EES); screening for energy poverty vulnerable areas.
   - *Supply applications*: Location and sizing of district cooling/heating systems; model the performance of micro grids; evaluate the impact of local renewables and storage.

2 Municipal urban planners: Working with top-down decision makers, urban planning officials need to translate general policy into specific interventions, by defining and enforcing regulations for buildings, streets, etc. In Boston this role is performed by the Boston Planning and Development Authority (BPDA). In this context the BPDA could use an UBEM to check if a new proposed development would fit within the power supply conditions in a district, and define zoning regulations accordingly by building archetype. Furthermore, it could provide developers with calibrated baseline archetypes and require their use for compliance.

3 Local energy providers: Although not directly involved in making policy in the US, utilities distributing power to buildings and local generators are a key stakeholder. In other countries energy providers might even be public institutions (Kuwait) giving them even more relevance in decision making. They have exclusive access to detailed demand data, decide energy prices, and are typically in charge of designing and maintaining distribution networks. In the city of Boston

this role is mainly occupied by two local utilities: Eversource (electricity) and National Grid (gas). However, as distributed generation through urban plants or solar panels is becoming more common, new smaller stakeholders will join the ecosystem. From their perspective, a calibrated UBEM can be an extremely valuable tool which can used to quantify the impacts in the network of the demands resulting from extreme events such as heat/cold waves or large new developments. Furthermore, an UBEM of the existing city can allow them to better target customers to offer specific programs or services.

4 Urban designers: Either working within private companies or a municipal department, an urban design team can take energy performance into account when making a proposal. A proactive planning department might be interested in defining energy requirements for a design team, ranging from the mandatory use of existing certification schemes such as LEED [47], to the compliance with peak demand limits. In this context, designers can develop their own UBEM models while applying archetype definitions provided by the city as the baseline for compliance.

5 Property owners and occupants: Last but not least, the owners and users of real estate, customers to energy providers, can become a key stakeholder for the development of UBEMs, since they can provide both building and demand validation data to the city. In the case of large portfolio owners such as hospitals or universities, their relevance is even larger since they typically have a say in urban energy policy, and in some cases, have their own generation and supply networks. From their perspective, the results of a calibrated UBEM, if made available as a public database or map, offer a tool to evaluate properties, and communicate with the city.

Given the extensive data requirements of a calibrated UBEM, for these applications to be possible, all the described entities need to be able to share information regarding buildings and metered data. A schematic framework of collaboration can be defined based on some of the modeling components defined in previous chapters. Figure 6-2 shows a diagram for the elements and relations which, in the opinion of the author, are necessary for such a framework to work. The municipality would commission an UBEM for the city or select districts, and develop a basic library of archetypes for buildings and occupants customized to the city or region. The geometry database for the model would be stored in GIS or cityGML format by the planning department, while archetype definitions would exist in an open format text file such as the proposed JSON template library. Model results and archetype definitions would then be made available for all other stakeholders, while the model itself would be only used by municipal officials in house. In terms of calibration, local providers would then provide metered samples of demands by archetype, non-anonymized, only for municipal modelers to use and never to be shared with other parties. In exchange they could request from the city the analysis of specific infrastructure proposals or future demand scenarios, using the municipal model.

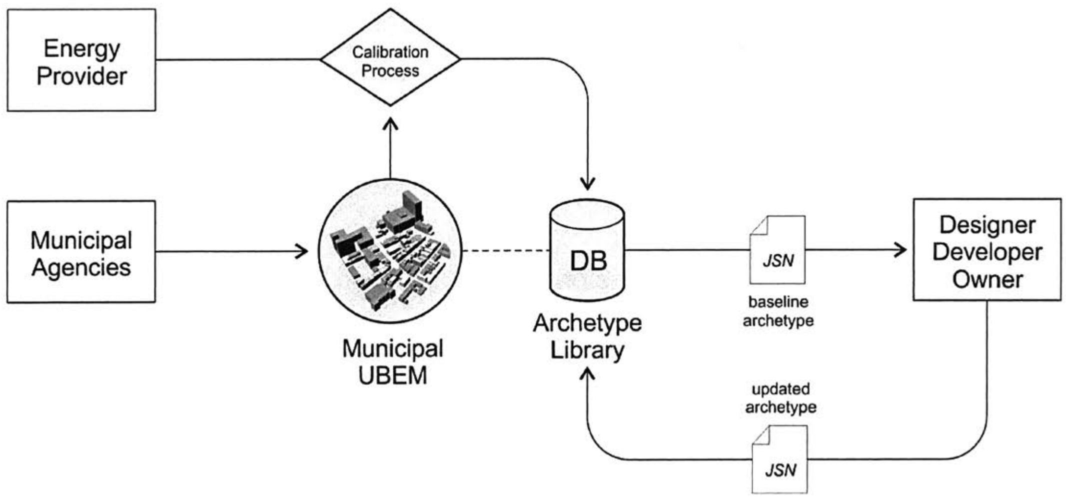



*Figure 6-2: Data framework diagram for the maintenance of a municipal calibrated UBEM*

Once calibrated, archetype definitions would be provided to other stakeholders for purposes of urban design and planning, to be used in separate design UBEMs. For example, after finishing a new building or design proposal, both design teams and real estate developers would provide back information of the new buildings in the same format to the planning department, updating the model. Setting up such a system is a complex effort that would require changes in current urban data systems and commitments from multiple stakeholders. In terms of technology/data requirements, a city like Boston would have to address all limitations described in Chapter 3 regarding geometry and building data, and create a live repository of archetypes to characterize its own building stock. Additionally, the planning department would have to staff an in-house team of modeling experts to run and maintain the model. Finally, agreements would have to be reached politically with local energy providers to determine the exact conditions and privacy requirements under which building and energy data is shared and maintained. Solving these implementation requirements is outside of the scope of this dissertation. Instead, the following sections provide to case studies of what could be accomplished with such a municipal calibrated UBEM.

### *6.2.2 CASE 1 - Energy pricing policy in Kuwait*

As introduced in Chapter 4, residential buildings are responsible for a majority of electricity consumption in Kuwait. Peak demands, 60% of which are the result of space cooling and air conditioning, already bring the city's energy system to a point of unmanageable stress every summer, which results in power cuts and constant repairs [149]. Given the growing number of government housing applications and the increase in temperatures due to climate change, these demands are only expected to increase. As part of its 2030 Climate Action plan, the country has committed to reduce residential energy use by 15%, through efficient new construction and building retrofit programs. One of the key policy strategies under consideration is the change from the current uniform electricity pricing system into a tiered one.

In the present situation, the Kuwaiti government heavily subsidizes energy, paying for about 90% of the generation costs, and has maintained an extremely low flat rate for residential users since 1966, equivalent to 0.001 $/kWh (compared for example to 0.14$/kWh in Boston). The increase in prices and the introduction of tiers would theoretically reduce consumption and increase the motivation of home owners to upgrade the building stock through retrofit interventions. In this context, an UBEM can be applied for the detailed analysis of the buildings in different city districts, to better evaluate the potential savings of some of these strategies.

To do so, the UBEM of AlQadisyah developed in Chapter 4 is applied to simulate and compare three retrofit and two energy-pricing scenarios [176]. In order to evaluate the advantages of a calibrated UBEM, occupant related parameters are defined using two methods: Deterministic uncalibrated assumptions, referred to as the "Basic" case, and probabilistic calibrated variables, the "Stochastic" case. For this study, it is assumed that the municipality of Kuwait would have developed a citywide model of their residential building stock, and developed the required data collection and calibration presented in previous chapters. In this application case, three main types of urban stakeholders would benefit from the modeling exercise: A municipal energy planner interested in reducing demands, a local energy provider trying to target building owners, and a municipal policy maker, interested in implementation. Results are interpreted and compared from these three perspectives in Section 6.3.

Analysis scenarios

Based on the calibrated archetype library for the district, a suite of energy efficiency strategies (EES) can be proposed for evaluation. In AlQadisyah, these strategies range from simple and affordable to deep retrofits, and were defined in collaboration with local institutions. Table 6-1 lists the EES by increasing difficulty of implementation with estimated average cost in Kuwaiti Dinars (KD). For reference, at the time of writing 1 KD = 3.28 USD.

*Table 6-1: EES descriptions and associated costs (Materials and labor)*

| **Energy Strategies** | **Unit** | **Cost (KD)** |
|---|---|---|
| Facade weatherization | m2 | 0.16 |
| LED light bulb 80% replacement | item | 4 |
| Refrigerator replacement (EnergyStar eqv.) | item | 290 |
| Washing replacement (EnergyStar eqv.) | item | 240 |
| Dryer replacement (EnergyStar eqv.) | item | 140 |
| High efficiency AC system upgrade | ton | 185 |
| Exterior XPS insulation addition | m2 | 3 |
| Exterior finish paneled leaf addition | m2 | 18 |
| Window replacement with low emissivity | item | 145 |

For simulation, these strategies were grouped into three main retrofit scenarios. The first includes all EES related with the upgrade of lighting, appliances and cooling equipment, which could be implemented without heavy construction activities in the building. The second includes the retrofit of the building envelope to reach the 2010 code requirements [151] for insulation and materials, and the replacement of all windows which would also increase the general airtightness. Finally, the third combines all EES in a single in depth upgrade. The archetype parameter changes used to represent these scenarios for their simulation in the calibrated UBEM are detailed in Table 6-2.

*Table 6-2: Parameter upgrades by scenario*

| Parameter | Lighting Equipment | Envelope Glazing | Combined |
|---|---|---|---|
| Lighting Power (W/m2) | base x 0.40 | - | base x 0.4 |
| Plug Power (W/m2) | base x 0.84 | - | base x 0.84 |
| Wall / Roof U (W/mK) | - | 0.32 / 0.40 | 0.32 / 0.40 |
| Glazing U (W/mK) / SHGC | - | 2.33 / 0.65 | 2.33 / 0.65 |
| Infiltration rate (ach) | 0.4 | 0.4 | 0.4 |
| Cooling system COP | 3.3 | - | 3.3 |

In order to understand the affordability and economic feasibility of the scenarios, the previously referred energy pricing scenarios were modeled as well. In the first case, the current uniform electricity price of 0.002 KD/kWh was considered throughout the neighborhood. In the second scenario, a tiered pricing system is introduced, proposed by the Kuwaiti government in 2016, and under review at the time of this research. In this model, electricity rates range between 0.005 KD/kWh and 0.015 KD/kWh depending on monthly consumption (Table 6-3).

*Table 6-3: Current and proposed electricity pricing scenarios*

| Pricing | Consumption | Price |
|---|---|---|
| Uniform | Any consumption | 0.002 KD |
| Tiered | kWh/month < 3,000 | 0.005 KD |
| | 3,000 < kWh/month < 6,000 | 0.008 KD |
| | 6,000 < kWh/month < 9,000 | 0.010 KD |
| | kWh/month > 9,000 | 0.015 KD |

Simulation setting

All scenarios were simulated using the AlQadisyah UBEM developed in Chapter 4, based on a local GIS dataset for building geometry and a JSON template library file for the storage of simulation parameters. In the stochastic simulation case, the same four occupant-related parameters were considered as uncertain. Their calibrated joint distribution was sampled using a Latin Hyper Cube (LHC) approach.

For the three retrofit strategies plus a base case, each building was modeled using 100 samples. In addition, to calculate the distribution of total demands for the neighborhood, the resulting energy use distributions by individual building were subsequently randomly sampled 10,000 times and added together, assuming the 100 result values equally likely. Both aggregate and individual results were then used to calculate the energy and cost savings as discussed below.

Calculation of energy and cost savings

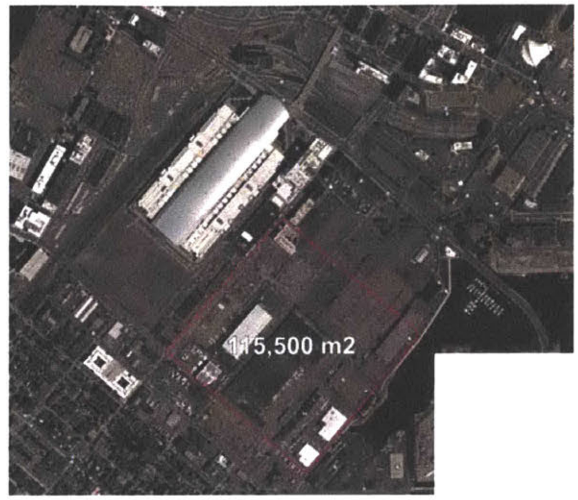
As a final step, simulated demands were processed both in the aggregate and by building, and cost savings were calculated by scenario for both energy use and costs. The final results were analyzed at three levels of aggregation, aligned with the perspectives of the three urban stakeholders discussed above. Based on this levels of analysis conclusions are drawn in Section 6.3.2.

1 *Total neighborhood demand:* Annual energy use per building was aggregated for each scenario, and compared for both the basic and stochastic modeling methods.
2 *Single building savings:* Annual energy and cost savings were obtained by building and compared for both methods and all scenarios. In the stochastic case, the likelihood distributions of savings were obtained using 100 samples.
3 *Payback time likelihood:* Simple payback times (PBT) were calculated for 100 samples by building. Cumulative distributions were obtained for each one, and the likelihood of a PBT to be equal or smaller than a given value ($p$), expressed as $P(PBT \leq p)$ was calculated. Finally, buildings were aggregated according to this likelihood value, for all scenarios.

### *6.2.3 CASE 2 - Energy efficient urban design in Boston*

As previously discussed, the City of Boston is deeply committed to reduce its GHG emissions and make its energy system more resilient as part of its Climate Action Plan. At the same time, the city is seeing its population grow significantly and is expected to overpass 700,000 inhabitants by 2030, a number not seen since the 1950s. To address this increase, the city published a new Housing Development Plan in 2014, with the central goal of adding 54,000 housing units in the next 15 years increasing the municipal stock by a 20% [177]. A majority of the projected units (44,000) will focus on housing the growing workforce, attracted to the city, between other factors, by an increase of available jobs related to innovation and technology. The Seaport District, has been designated by the Boston Planning and Development Authority (BPDA) as a new business center for the city, given its close relationship with the financial district and the airport, and has seen in the last 5 years most of the commercial real estate development in Boston. Following these developments, some of the still empty land in the area, is under consideration for the construction of new housing units (Figure 6-3).

Boston Seaport District




Proposal site by Convention Center

*Figure 6-3: Location of proposed housing development in Boston's Seaport District*

In the context of this research, this location was used as an urban design case study in a seminar class in urban environmental modeling co-taught by the author (with Prof. Christoph Reinhart) at MIT in the spring of 2016. The class, titled "4.433: Modeling urban energy flows" [178], required graduate design students (architects and planners) to develop a neighborhood proposal for the area. In this application case 3, a simplified version of two of the students projects are used as two hypothetical design proposals, and two UBEMs are created to compare their relative energy performance from two perspectives: The perspective of the urban designer interested in making the best proposal, and the perspective of the urban planner, setting energy requirements and guidelines for the district. In this application scenario, the UBEM models are not generated by the city but instead produced by the design team, using archetype definitions provided by the city. As with case 2, occupant related parameters are defined using two methods: Deterministic uncalibrated assumptions, referred to as the "Basic" case, and probabilistic calibrated variables, the "Stochastic" case. Constructions on the other hand are defined according to current energy codes in a deterministic fashion.

Design proposals and archetype definitions

Both proposals (A and B) occupy an area of land of 115,500 m2, delimited by D Street in the west and the waterfront in the east, and extend the existing street grid around the site, resulting in urban blocks of 5,000 to 9,000 m2. The limitations in terms of maximum height, number of stories and Floor to Area Ratio (FAR) for the site were defined as design requirements based on the current zoning of the BPDA [179]. In addition, a required number of building floor area and residential units were provided for the designers. In proposal A (based on the class project of Farrell, Cohen, Lin) the designers chose to design high density apartment buildings, allowing for more public spaces within the blocks and a public park in the center of the neighborhood. On the other hand, in proposal B (based on the class project of Bemis, Belanger, Chen, Mercuri) the designers chose a lower density solution trying to emulate the very Bostonian typology of row houses, typical in the neighborhoods of BackBay or SouthEnd. Larger apartment buildings were concentrated only in corner blocks and main streets, resulting in an overall higher Land Occupancy Ratio (LOR). Both solutions resulted in an equivalent built floor area and number of units (Figure 6-4). Table 6-4 summarizes the size and characteristics of the proposal.

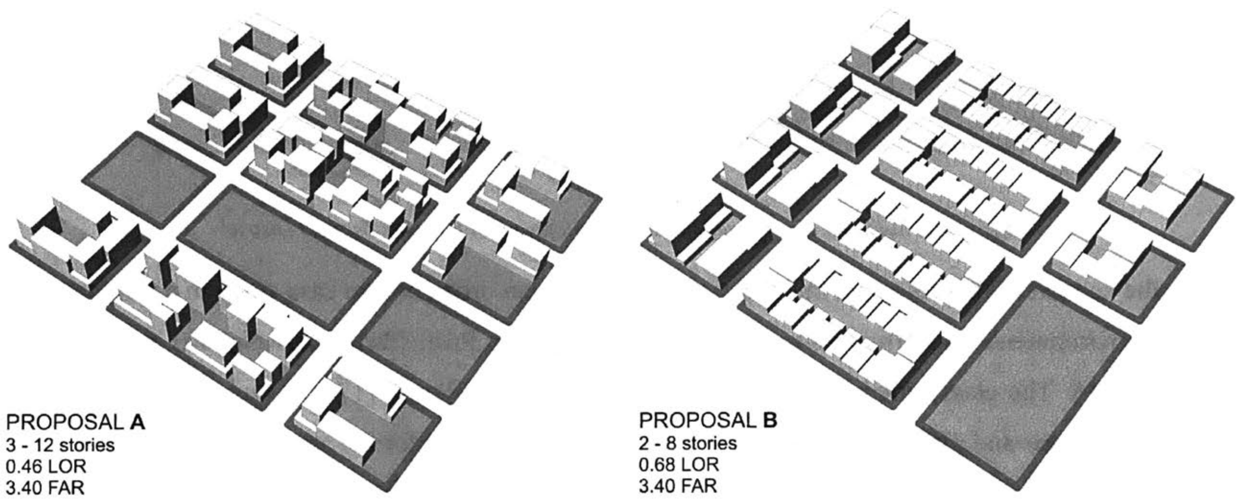



*Figure 6-4: 3D model of proposals A and B for a residential neighborhood in Boston*

*Table 6-4: Summary of geometric characteristics by proposal*

<table>
<tr><th>Proposal</th><th>Block Area (m2)</th><th>Built Area (m2)</th><th># Units</th><th># Stories</th><th>LOR</th><th>FAR</th></tr>
<tr><td>A</td><td rowspan="2">75,640</td><td rowspan="2">256,500</td><td rowspan="2">3,100</td><td>3 to 12</td><td>0.46</td><td rowspan="2">3.40</td></tr>
<tr><td>B</td><td>2 to 8</td><td>0.68</td></tr>
</table>

Regarding archetype definitions, all buildings were assumed to belong to a single family of multifamily residential structures. Given that all buildings on the project would be expected to be built in the present time, all envelope constructions and glazing systems were defined according to the requirements of standard ASHRAE 90.1 [45], currently required by the Massachusetts Energy Code. Systems performance coefficients for cooling and heating, as well as basic operation schedules and window to wall ratios were defined according to the Energy Simulation Reference buildings published by the US Department of Energy (DOE) [93,119]. Finally, occupant related parameters were defined following the same reference building definitions in the "Basic" modeling case, and following the calibrated parameter distributions developed in Chapter 5 for the case study of Cambridge, MA. Given the adjacency between Cambridge and Boston and the similar use types considered, the distributions were assumed to be applicable in this example.

Simulation setting and comparison metrics

In the analysis of both proposals, an UBEM was generated for each one using again the previously described modeling workflow. Archetype definitions were assigned using a JSON template library file, while in this case the 3D geometry of the buildings was manually modeled by the designers. In the stochastic simulation case, the six occupant-related parameters from Chapter 5 were considered as uncertain. Their calibrated joint distribution was sampled using a Latin Hyper Cube (LHC) approach and each building was modeled using 100 samples. In addition, to calculate the neighborhood energy certification metrics described below, the resulting energy use distributions by individual building were subsequently randomly sampled 1,000 times, assuming the 100 result values equally likely. In this case, results were analyzed using two metrics, aligned with the perspectives of the two stakeholders under consideration. Based on these levels of analysis conclusions are drawn in Section 6.3.3.

1 *Buildings energy use intensity (EUI):* From the perspective of a design team, interested in making the best proposal from a holistic point of view, energy efficiency is just one among many metrics to be considered including daylight access, public space quality, construction costs, etc. As part of this exploratory process, solutions are compared in relative terms. This means that in energy terms, the best proposal is the one that achieves the lowest consumption for individual buildings and for the neighborhood. Hence, proposals A and B are compared in terms of their total EUI and distribution of EUIs.
2 *EnergyStar building score:* From the perspective of a planner from the BPDA, working with a design team and defining the parameters that the proposal needs to fulfill, energy requirements will be expressed in absolute terms. Compliance might be required for the maximum peak electricity or gas load, a minimum number of hours when natural light or ventilation can be used, or a minimum performance level for every building in the neighborhood. In this case, the EnergyStar score system developed by the US Environmental Protection Agency (EPA) [180] was chosen for the analysis. EnergyStar will give a building a score between 0 and 100 depending on how its energy use compares with that of a median national building of the same type. To acquire the EnergyStar certification, a score of 75 needs to be achieved. It was assumed that the BPDA required all buildings in the neighborhood to fulfill that requirement.

## 6.3 Results

In the following sections, the results of the application cases for UBEM are presented and discussed in detail from the perspectives of the previously mentioned urban stakeholders. In each case, the advantages of calibrated UBEMs are highlighted, reinforcing the practical value of the method.

*6.3.1 Savings by scenario in CASE 1(Kuwait)*

Total neighborhood demands

The evaluation of the simulation results for all energy efficiency strategies (EES) can be conducted from multiple points of view. For the local municipality energy planner, overall energy reductions from all buildings are particularly relevant in order to plan for future GHG emissions and sufficient generation. In order to make results more generic, the aggregate energy use intensity per conditioned floor area unit was calculated for the neighborhood for the three strategies plus the current scenario.

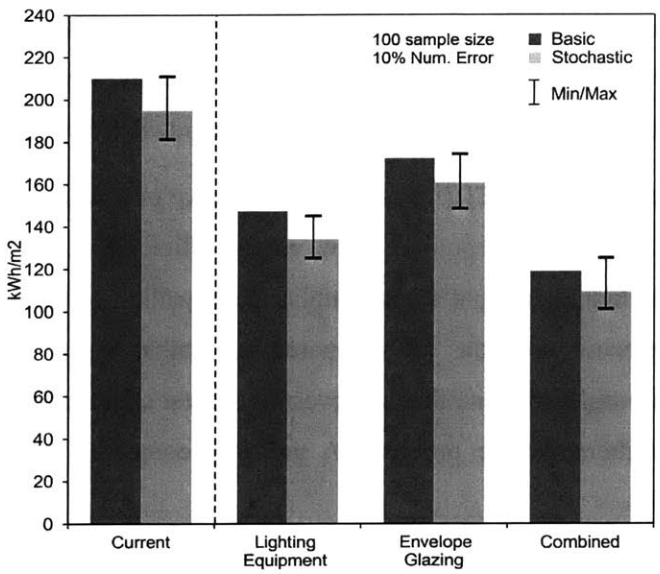



*Figure 6-8: Total normalized energy use by scenario*

Figure 6-8 represents the total EUI calculated through the basic and stochastic methods, as well as the minimum and maximum values obtained from the sampling in the latter. A numerical error of a 10% is considered, given the limited sample of 100 simulations. Regardless of the method considered, the lowest EUI value is always achieved by the "combined" scenario, followed by "lighting/equipment". The results show that, on average, the basic model slightly over predicts energy use by a 6 to 8%, consistent in all cases when compared to the stochastic result. It also shows that the maximum variance in the total demand stays within a ± 8% in all cases, plus a 10% numerical error with the basic result lying within that uncertainty range. When the demand results were translated into relative savings compared to the current scenario, the resulting uncertainty was even smaller, within a total ± 4%. Based on these results, a citywide energy planner can understand how far each strategy would have to go in order to guarantee a certain reduction, and basic archetypes would be sufficient since the stochastic modeling does not really add any new information for decision making. The following results jump to the scale of individual building conditions to provide insights about implementation and savings.

Disaggregate building savings

The earlier discussed energy savings assume that any of the three scenarios would be adopted across all buildings in a neighborhood. Since the decision to retrofit a building remains with its owner, it is also necessary to understand the range of savings that can be expected by building from an EES, so that municipalities and utilities can consider the owner's perspective. Stochastic and basic savings were calculated by user and compared for by pricing scenarios. Figure 6-9 shows the energy use and cost savings for a sample building, a two story 60s villa, to illustrate the differences between methods.

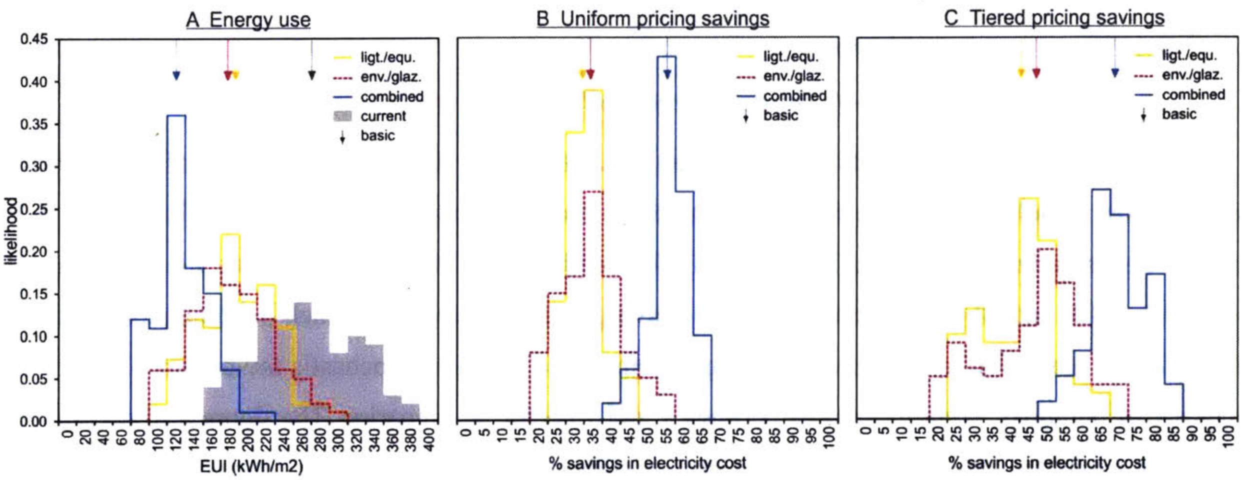



*Figure 6-9: EUI and energy cost savings by scenario for sample building "42k"*

According to the stochastic model, the current EUI distribution (Figure 6-9A) of the building ranges between 140 and 380 kWh/m2, a variation of ± 45% over the deterministically predicted EUI of 270 kWh/m2. While the basic EUI values agree with the mean stochastic result in each scenario, uncertainty ranges remain comparably large. Results also show that for this building, "LGT/EQU" and "ENV/GLZ" scenarios result in almost identical EUI distributions. The large uncertainty in energy use translates to the predicted cost savings presented in figures 6-9B and 6-9C. In both cases, the largest savings according to the basic model are achieved by the "Combined" scenario, with very similar savings distributions for the "LGT/EQU" and "ENV/GLZ" respectively. With uniform pricing, the stochastic model agrees in the average (PE < 3%), but shows a 38% smaller uncertainty in "LGT/EQU" compared to "ENV/GLZ", presenting it as a less risky option. The relevance of the stochastic model becomes even more evident with tiered pricing, since lower EUIs for the same user will result in lower prices. The basic model predicts savings 30% higher than with uniform pricing in all scenarios, failing to capture the different possible pricing situations for a building. The stochastic model shows a much larger uncertainty, with the increase in savings ranging from 0% for the highest EUIs, to 15-20% in the best case.

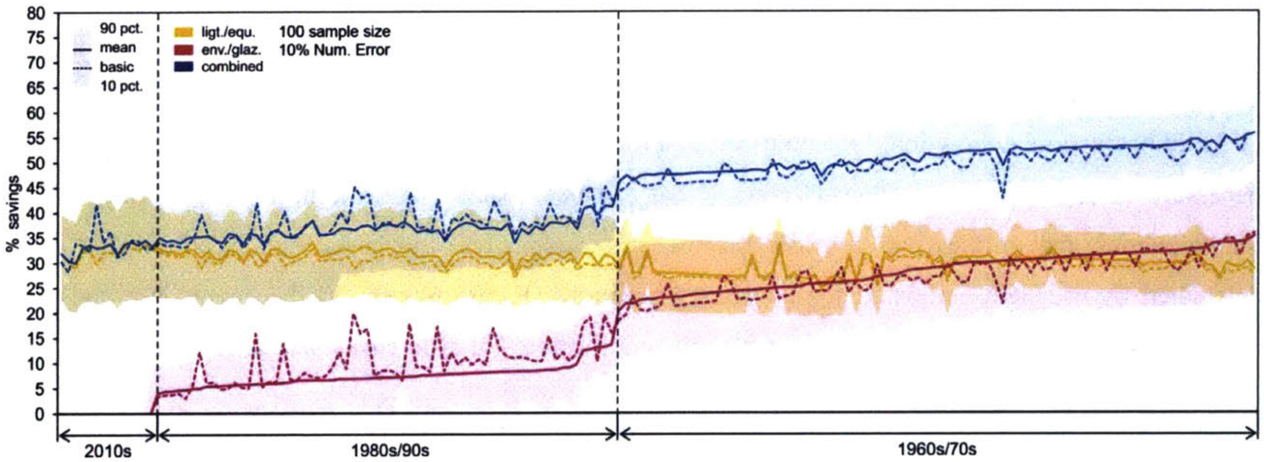



*Figure 6-10: Energy cost savings by building with uniform pricing*

This example building results show the need for a stochastic model in the analysis of tiered pricing implications, to help identify the number of buildings likely to change tier with a retrofit. Figures 6-10 and 6-11 summarize results for all buildings in the neighborhood. Figure 6-10 shows the mean ($\mu$), 10 percentile (p10) and 90 percentile (p90) relative savings were calculated for each building along with the deterministic prediction for the current pricing system. Basic and mean stochastic savings are close for the majority of buildings, with differences between 1 and 13% for all scenarios. The figure also reveals that buildings from the 1960s/70s tend to present significantly higher estimated savings from envelope upgrades than more recent buildings. Figure 6-11 shows corresponding results for tiered pricing. In this situation, basic and mean stochastic methods diverge between 6 and 35% for different buildings. As with the individual building example, the basic case can only consider one tier by building, misrepresenting its potential range of savings. Additionally, the stochastic model shows larger variation between the uncertainty ranges in buildings, with differences between p10 and p90 of 6-37% savings.

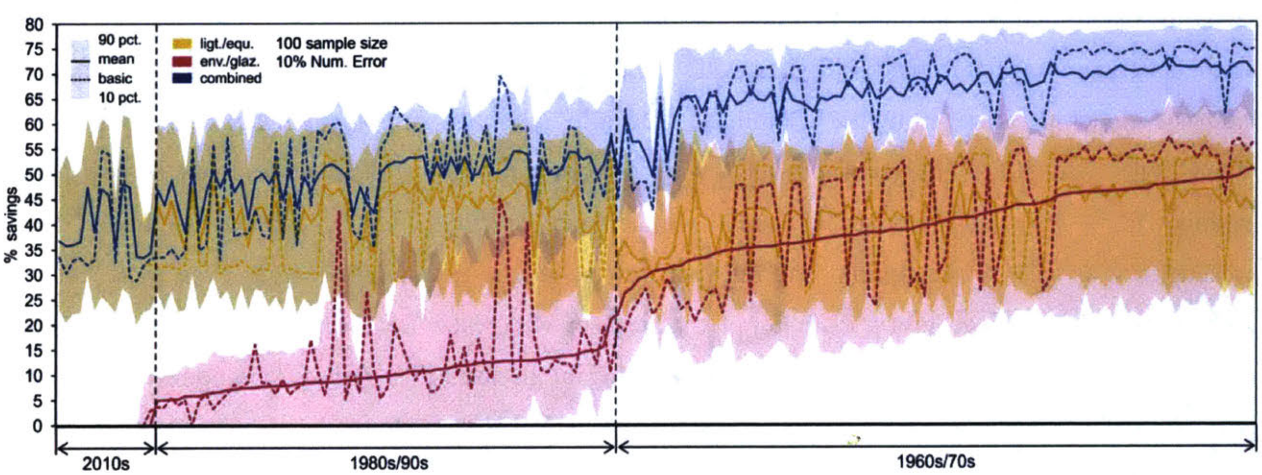



*Figure 6-11: Energy cost savings by building with tiered pricing*

Based on the uncertainty in savings, buildings can be classified and targeted differently. For example, for those in the right of the graph, the "combined" scenario might be worth pursuing, while for those on the left, "LGT/EQU" seems the best option. This type of information is especially valuable from the perspective of any local utility or company targeting customers, because even without providing definitive results by building, it allows a detailed screening about risks associated with new technologies or services at the scale of a neighborhood.

Payback time likelihood analysis

While occupant related uncertainties can help energy providers and third parties to target buildings based on potential savings and reduced risks, owner decisions to apply the proposed EESs will depend on the implementation costs. The probabilistic results of a calibrated UBEM become especially useful in this context, since they allow those defining implementation policies to understand the likelihood of a particular EES to stay affordable for a building. To illustrate this idea simple payback times (PBT) were calculated by building and by scenario for 100 parameter samples, using the implementation costs described previously. Then, in order to mimic a decision making process, the likelihood distribution per building was used to calculate the PBT value met in at least 80% of the parameter combinations sampled. This limit was chosen as a confidence interval allowing the decision maker to judge the viability of the retrofit scenario with one number per building. Next, based on these 80% likelihood values, the cumulative distribution for PBT was obtained for the complete neighborhood in each scenario and pricing scheme. All cases were finally compared against a maximum PBT of 10 years i.e. it is assumed that for an owner to consider an EES it had to achieve a 10 year or lower PBT in 80% of cases.

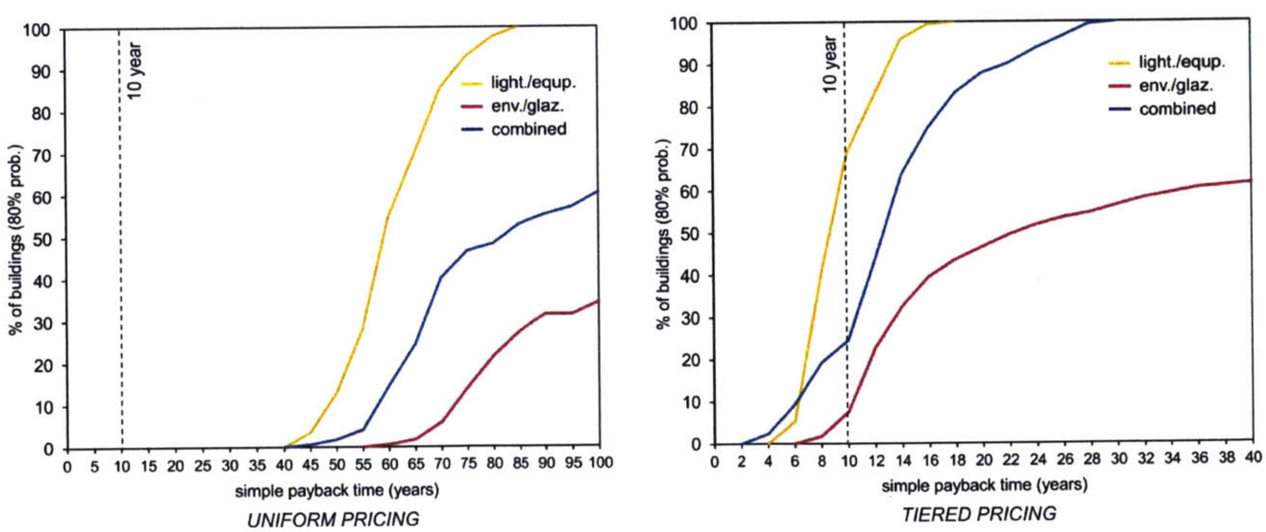



*Figure 6-12: Cumulative PBT distribution (80% likelihood) with uniform pricing*

Figure 6-12A compares the resulting distributions assuming uniform pricing, and clearly shows that with the current very low energy prices in Kuwait (0.002 KD/kWh) no retrofit scenario is affordable enough, with PBT values starting at almost 40 years. Putting aside the unreasonable PBTs, the graph also shows that the larger implementation costs necessary in envelope upgrades reduce their estimated implementation rates, compared to the "LGT/EQU" scenario, which is the more affordable option for any chosen payback time. The potential introduction of tiered pricing raises rates significantly above the uniform pricing scenario, between 2.5 and 7.5 times more depending on the tier, and hence increases the financial appeal of the retrofits. In Figure 6-12B, PBT likelihood distributions are explored for the tiered pricing scenario. The higher prices result in much smaller PBT values, in many cases under the 10 year mark, but which still do not cover all buildings. A majority of buildings (68%) can meet a PBT $\leq$ 10 (At least 80% of the time) in the "LGT/EQU" scenario, followed by a 24% in the "combined" case and a 7% in "ENV/GLZ". This result seems to suggest that the "LGT/EQU" scenario is the most effective to pursue, unless a higher PBT is allowed. The total demand reduction in the neighborhood seems to support this option as well, but the PBT analysis showed it would only be feasible under higher tiered rates. If the policy maker wanted to guarantee that 100% of buildings could access a reasonable PBT, then the pricing tiers would have to be modified, and the UBEM model could assist in their iterative analysis.

### *6.3.2 Energy metrics by proposal in CASE 2 (Boston)*

Total neighborhood demands and EUIs

After simulating via UBEM the energy use for each building using "Basic" and "Stochastic" techniques, normalized EUIs were calculated and analyzed by proposal. As described in the methodology, from the perspective of a designer solutions are compared mostly in relative terms with goal of minimizing the total energy and EUI by building. While in this case we are considering energy metrics, the same would be true for any other simulation related results such as daylight access or GHG emissions. To support this approach EUI results were first mapped by building for the "Basic" modeling approach (Figure 6-12). As long as the considered occupant related parameters are representative of the average, deterministic archetypes are sufficient for comparing design solutions, and identifying the worst performers in terms of building geometry and orientation. In this case, results show that in both proposals EUIs range from 120 to 190 kWh/m2. In proposal A, the less compact structures have the highest EUIs, while in B the desired row houses seem to perform poorly compared to the rest of buildings. From this deterministic analysis the design team can start making decisions about specific sections of the proposal, or combine it with parametric geometry studies to identify optimal massings, window to wall ratios by orientation, or urban densities.

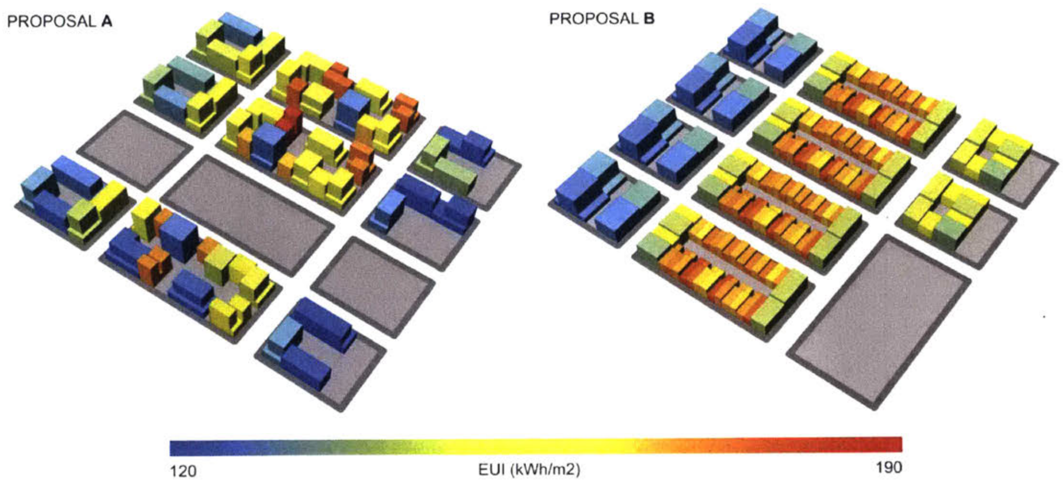



*Figure 6-12: "Basic" case EUI results by building for proposals A and B*

Next, results were considered for the proposal as a whole, for both "Basic" and "Stochastic calibrated" models. Figure 6-13 shows the resulting EUI distributions for both proposals, and Table 6-5 the total EUI for the complete neighborhood. Regardless of the modeling method, proposal A shows lower energy use. According to the Basic case, the mean EUI for A is only a 5% better than for B, with values of 147 and 154 kWh/m2 respectively. A similar improvement can be found in the total demands (Table 6-5). Additionally, when considering individual EUI distributions, proposal A includes some of best and the worst performing buildings, with 30% higher standard deviation that proposal B. Given how similar the results for both proposals are, a designer might prefer to choose proposal A and improve the design of the worst performers. The Stochastic results provide additional information regarding what the real distribution might look like, depending on occupant behavior. In terms of mean building EUIs, the relative improvement of A over B is effectively the same (6%), but in absolute terms both distributions show higher overall values with means of 177 and 189 kWh/m2 respectively, after calibration of occupant parameters. Results also show a much larger diversity of demands with EUIs as low as 80 and as high as 280 kWh/m2. However the difference in deviation between proposals largely disappears. When considering the total demands, proposal A was again 5% better than B in every situation (Table 6-5), but in both energy use was an 18% higher than in the deterministic uncalibrated case. Given these small differences between proposals, a designer focusing on a relative comparison would still go with proposal A, or potentially let metrics other than energy drive the design.

*Table 6-5: Summary total EUI distributions by proposal and modeling case*

| | Basic Case (kWh/m2) | Stochastic Case (kWh/m2) | | |
|---|---|---|---|---|
| **Proposal** | **Single Result** | **Mean Total** | **Min Total** | **Max Total** |
| A | 142 | 168 | 152 | 183 |
| B | 149 | 175 | 165 | 186 |

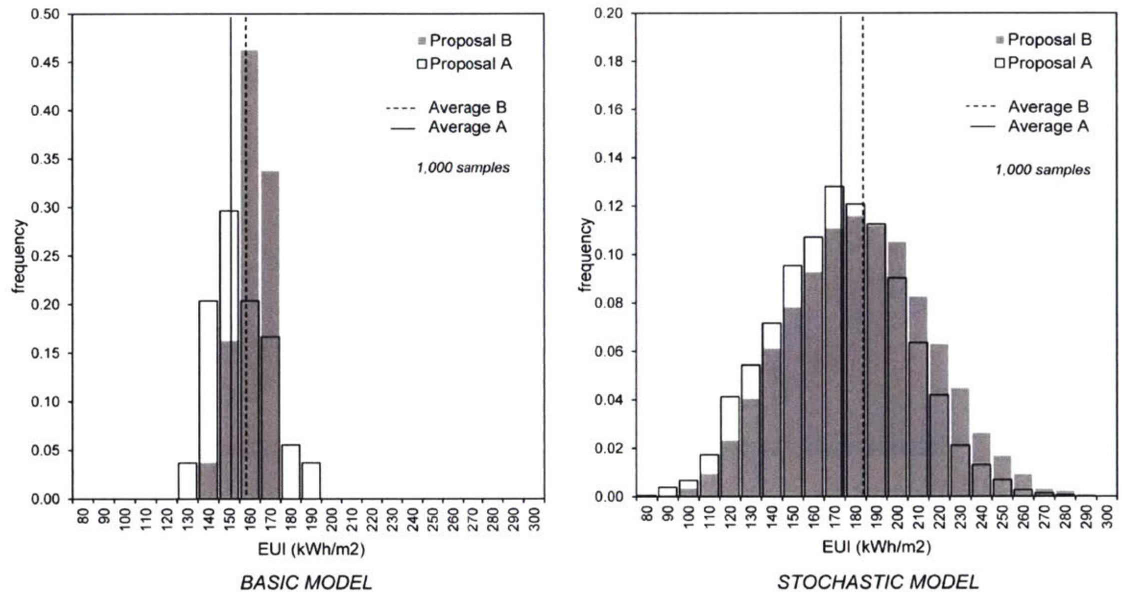



*Figure 6-13: Simulated building EUI distributions for proposals A and B by modeling case*

<u>EnergyStar score likelihood analysis</u>

While designers might be mostly interested in relative performance improvement, a hypothetical local planner or regulator would need to set specific absolute performance targets to accept or reject a particular proposal. For this example, we have chosen the US EPA EnergyStar score (0-100) as the regulation metric, with minimum value of 75. A BPDA planner could require designers to make sure that a certain percentage of the buildings or units achieve the target. For this case study, we will assume a requirement of 75% of the buildings. Based on the basic deterministic model, both proposals would fulfill the requirement with scores that range between 90 and 100 for every building.

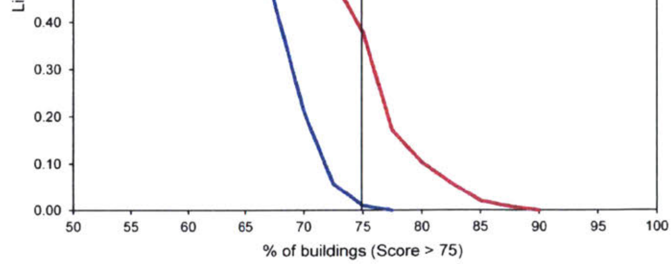



*Figure 6-14: Likelihood of buildings with a score over 75 for proposals A and B*

However, EnergyStar scores are based on the real energy use of the building, and are hence influenced by occupant choices. In order to make the certification requirement more effective, the local planner could provide calibrated UBEM archetypes to the designers/developers and require their use for compliance. In this scenario, EnergyStar scores were calculated for 1,000 samples using the stochastic model. Figure 6-14 shows the resulting likelihood for a percentage of the buildings of obtaining a 75 score, compared to the target. Proposal B would achieve the requirement with less than 5% likelihood. Proposal A would reach it with a likelihood of 40%. The large difference indicates in this case that Proposal A is more robust against changes in occupant parameters, and has a lower risk. Based to these results the design team would most likely choose proposal A. The planner on the other hand, given the relatively low likelihood of 40%, could either accept it as sufficient, or require the design team to improve the proposal, until it achieves a higher acceptable likelihood of reaching the 75% buildings target.

## 6.4 Discussion

Based on the results from the two example cases of application, this section discusses the potential application of the UBEM data framework proposed, and the relevance of calibrated stochastic archetypes in policy and urban design decisions.

### *6.4.1 UBEM applications and stakeholders*

As discussed in the introduction, a calibrated UBEM can provide building scale information about potential energy retrofits, technologies and policies, helping cover the information gap that exists between long-term urban goals and the specific implementation strategies they require. To achieve that goal, modelling workflows have to adapt to the data needs and scale of work of different urban stakeholders, as identified in the methodology. A very general framework of data exchange was described for that purpose, in which it would be the role of a municipality to produce and maintain a calibrated UBEM and archetype library, with the collaboration energy providers and real estate owners. However for the viability of such model, it has to be shown that such model would provide actionable information, useful for all stakeholders involved. Based on the results of the two example case studies in Kuwait and Boston it is possible to identify application scenarios which fulfill this requirement.

On an aggregate scale of analysis, a calibrated model can inform policies for emission reduction planning by evaluating the potential savings of different energy technologies in the mixed building stock of specific urban areas. This application is relevant from the perspective of a municipal policy maker, as shown in the Kuwait example where the total energy savings of energy efficiency measures where quantifies for a complete neighborhood. As described in the results section, deterministic basic archetypes are sufficient at this level of analysis.

In a more detailed scale, UBEMs can be applied for targeting buildings, in order to identify which specific structures or blocks might gain more from a particular intervention. At this scale the characterization of occupant uncertainties can help quantify implementation risks or outliers. This is the perspective of power providers and other third parties which need to interact with specific building owners. In the Kuwait example, the local utility could learn from the model about the distribution of potential customers in the neighborhood, and classify them based on size and period of construction. In addition, given its direct relationship with individual users, the company has the opportunity to reduce the model uncertainty by gathering building information through owners, or to even offer modelling services. Also in the Kuwait case, the exercise showed that an UBEM can help those developing policy implementation strategies, regarding energy prices, efficiency incentives, etc. The results analysis showed how the calibration of occupant parameters is necessary to understand the likelihood of a retrofit being adopted under a particular pricing scheme; something deterministic models cannot address. This type of analysis can be enriched with demographic, economic and social modelling, to further study adoption rates and affordability in collaboration with other areas of local government.

Finally, the example presented for Boston showed that in the analysis of two massing options for an urban design proposal, an UBEM can provide information about total energy use and help identify best and worst performing buildings. Furthermore, the comparison demonstrated that the use of deterministic literature based archetypes can mislead the designers, presenting both proposals as equivalent when in fact one of them performed a 15% better in almost all situations. Hence, a calibrated set of archetypes can be very useful for urban design by providing more realistic baselines for analysis, and giving designers a sense of the robustness of their proposals. The calibrated models were also shown to be valuable for urban planners and regulators, allowing them to develop better performance requirements and metrics to account for the likelihood of a design to achieve them.

While having different objectives, all these urban actors are necessarily intertwined. For that reason, the author believes that they would all benefit from the existence of a common energy-modelling infrastructure, which facilitates the exchange of information about model parameters, and the evaluation of policies at multiple decision scales. The effort level required to build such framework is of course significant, especially in terms of the gathering of building and energy data, and securing the commitment of all stakeholders to participate. In order to scale up the use of UBEMs, institutional support for data collection will be fundamental and further research need to explore basic dataset requirements, minimum sample sizes, integration with regional supply models, and data privacy concerns. Nevertheless, the results presented here paint a positive image of the potential applications and insights they have to offer.

### *6.4.2 Value of calibrated stochastic archetypes*

The advantage of using probabilistic variables to define occupant parameters in an urban model is the capability of taking into account the modeler's large uncertainty regarding types of users and their behavior. If such variables are calibrated as proposed in previous chapters, UBEMs can more effectively represent existing demand extremes and predict how they will be affected by potential energy policies. However, they also require extensive data about existing energy demands and building characteristics, and significantly more computational power. Based on these results, are there analysis scales at which the additional complexity is not necessary? This study has shown that when considering total energy demands and savings at the scale of 100-200 buildings, the variability introduced by the uncertainty in occupant parameters is very small. Small enough that a simpler deterministic approach in which parameter assumptions and vetted against local expert knowledge can be used to prioritize energy solutions. When moving from aggregate analysis, to the level of policy implementation or performance compliance by building, the results have shown how a deterministic model can misrepresent the annual demands of individual buildings, and as a result, over predict the potential savings of tiered pricing (Kuwait) or the certification scores of proposed buildings (Boston). Such discrepancies, which would only become larger at smaller timescales of analysis, can lead decisions makers to misplace incentives in strategies with very small likelihoods of adoption, or misjudge new developments. Further research about the number of samples required to explore a future scenario and, about additional sources of uncertainty such as the climate, will be necessary to make stochastic UBEM fully effective in decision making.

Furthermore, calibrated uncertain parameters allow decision makers to evaluate the implementation risks associated with a particular energy policy or scenario. In the case studies previously presented it was assumed that energy efficiency measures were adopted by all building owners in an instantaneous manner. However, in a real implementation scenario building upgrades or new buildings will be adopted through time, as a result of financial incentives and socioeconomic context. The likelihood information associated with simulated scenarios can be combined with technology adoption models in order to estimate schedules of policy adoption, necessary for long term planning on the side of municipalities and utilities. In further research, probabilities of adoption by energy strategy, which are often published by national governments, will be studied as a function of the payback time likelihoods as calculated in this chapter, with the goal of estimating the number of years required to reach a certain energy target. Energy prices and climate changes through time should also be taken into account. In addition, modern community dynamics modeling could potentially be combined with UBEM likelihood results to map at an urban scale how the proximity between technology adopters might affect the general implementation.

## 6.5 Summary

The previous sections introduced the main urban stakeholders who would benefit from applying calibrated UBEMs in decision making, and explored some these applications in two example studies: The evaluation of energy efficiency policies in a Kuwaiti neighborhood, and the comparison of two urban design proposals in Boston. The key findings of this exercise are:

- A calibrated UBEM model can provide actionable information for urban decision making, for a variety of stakeholders, including municipalities, energy providers, and designers.
- In terms of total energy demands for policy or design scenarios, UBEMs derived from deterministic and calibrated stochastic archetypes produce very similar results, with mean differences below 5%.
- When comparing energy demands by building, especially when considering absolute performance targets such as pricing tiers or maximum EUIs, UBEMs based on deterministic archetypes are not sufficient and stochastic models need to be taken into account.

Chapter 7

# Conclusions and outlook

As the dissertation concludes, this chapter revisits the introductory hypothesis from chapter 1 and provides a general outlook for future research in the field of Urban Building Energy Modeling.

## 7.1 Conclusions

### *7.1.1 Summary of contributions*

The research developed as part of this dissertation, started with a review of the current state of the art in the nascent field of Urban Building Energy Modeling (Chapter 2). As a result of this exercise, the author proposed three main research hypotheses which have been addressed in this work as follows.

**Feasibility**

In Chapter 3 a citywide UBEM was generated and simulated for the city of Boston, with over 80,000 buildings, using only currently available public datasets. Buildings were characterized through 52 deterministic archetypes, classified according to programmatic use and year of construction. An automated modeling workflow was developed, and a new template library file format was introduced for the storage and exchange of archetype definitions. Annual and hourly demands were obtained by building, fuel type and end use. The process showed that while feasible, the generation of such model is a time consuming effort, requiring more than 400 hours of work and 50 hours of simulation time. Key barriers for the large scale implementation of UBEM in US cities were identified, including the inadequacy of available geometric data, the need for a unified data ID at the scale of buildings, and the lack of locally collected constructions, occupant and energy data. These limitations notwithstanding,

> *this work has shown that it is possible to generate and simulate a citywide UBEM and a library of building archetypes using available municipal urban datasets.*

**Reliability**

Chapter 4 introduced a new calibration approach for UBEMs, which applies principles of Bayesian statistics to reduce the uncertainty in archetype parameters defined stochastically. As part of the method, the likelihood of a particular parameter distribution is estimated based on a simulation error analysis for a subset of buildings within an archetype, using measured energy data. The method was applied to model a residential district in Kuwait with 323 annually metered buildings characterized through four age based archetypes. Four occupant behavior related parameters were identified and calibrated using a subset of 164 buildings. The resulting calibrated statistical archetypes were successfully used to model the Energy Use Intensity distribution of the remaining 159 buildings. The presented validation showed that it is possible to characterize all structures belonging to a single archetype based on a limited metered sample of 100-200 buildings, as long as occupant behavior and demographics in the learning sample are representative of the whole group. These findings show that:

*Bayesian statistics can be effectively combined with UBEM simulations for the calibration of archetype parameters, using metered energy data of a representative subset of buildings within that archetype's population.*

The Kuwaiti case study district was also modeled applying three existing methods for archetype definition, with no calibration, where parameters were characterized both deterministically and stochastically based on available data sources. Simulation results showed that calibrated archetypes could effectively reproduce the real annual EUI distribution for the neighborhood, with errors lower than 5% in the mean and 15% in the $10^{th}$/ $90^{th}$ percentiles of the distribution. The obtained error range is equivalent to that recommended by ASHRAE Standard 14 2002 for the calibration of BEMs. Furthermore, the calibrated model achieved a 30-40% error reduction over common deterministic models.

*This work has shown that a calibrated UBEM can reliably reproduce annual EUI distributions for a neighborhood, with more accuracy than existing archetype modeling approaches.*

In Chapter 5 an expansion of the calibration method was developed for cases when monthly metered data is available, by introducing combined error metrics for the monthly mean and coefficient of variation. The method was demonstrated in the UBEM modeling of a sample including 2,662 residential buildings in Cambridge, MA. A subset of 399 buildings was used for the calibration of six archetype parameters using both annual and monthly data. Simulation results showed that while both techniques achieved equivalent accuracy when compared to the measured annual EUI distribution, only monthly calibrated parameters provided a good fit for monthly EUI distributions by fuel type. The calibration process also demonstrated that as the number of parameters and buildings considered increases, UBEM simulation can be combined with statistical surrogate meta-models to allow for sufficient sampling.

*These findings demonstrate that a calibrated UBEM may provide reliable predictions for EUI distributions, up to the temporal resolution of the available metered energy data.*

**Relevance**

Finally, Chapter 6 proposed a framework of collaboration between local governments, energy providers, urban designers and real estate owners, to make the development of municipal calibrated UBEMs possible. In the context of that collaboration, two application examples were implemented for the evaluation of energy policies in Kuwait and the comparison or urban design proposals in Boston. In the former, three energy efficiency strategies under two electricity pricing scenarios were compared for the calibrated UBEM in Kuwait (Chapter 4), analyzing results from the perspectives of an energy planner, a utility company and a policy maker. In the latter, two design proposals for a new residential neighborhood were simulated applying previously calibrated parameters (Chapter 5), and evaluated from the perspectives of a design team and a local urban planner. The results of both case studies showed that calibrated stochastic UBEMs provide actionable insights regarding future urban energy scenarios, especially when compliance of individual buildings particular targets – such as Energy Star compliance – is desired or when slight variations leads to non-linear price jumps such as in tiered pricing market. If, on the other hand, decisions are based on relative comparisons of aggregate demands for a neighborhood, UBEMs based on deterministic average archetypes were proven to be sufficient. Taken together, these findings demonstrate that:

*a calibrated archetype-based UBEM can be used in the analysis of policy and design scenarios, to provide actionable information for municipalities, energy providers and designers.*

### *7.1.1 Scope and limitations*

The set of UBEM methods presented in this dissertation, have been proposed as generic solutions to be used in the modeling of neighborhoods and cities worldwide, and for the evaluation of any building related energy scenario. However, the previously summarized conclusions have only been demonstrated within the specific conditions of the considered case studies. Their application outside of that scope will require further research and validation, which addresses the following limitations:

- The feasibility study of citywide UBEMs has been developed in the context of a typical municipality in the United States, and hence barriers and limitations described will vary in other countries depending on the specific local urban data practices and sources.
- The effectiveness of the Bayesian-based calibration approach in characterizing occupant related parameters has been proven so far in the modeling of low to mid rise residential buildings. The principles behind the method stay true for other building types and uses, but additional experiments will be required to understand if equivalent accuracy levels can be achieved in those cases. This is especially relevant in the case of mixed-use buildings, in which further subdivisions of the building massing will be necessary in order to assign multiple archetypes within a single structure. Similarly, the method has been tested in two relatively extreme climates, heating dominated in Cambridge and cooling dominated in Kuwait. Its implementation for the analysis of energy demands in a mild climate might be less effective than shown in this work, since heating/cooling loads will be less relevant in the overall energy use of the buildings. Further research is required in order to understand the most relevant parameters to be considered in any of these alternative modeling conditions.

- In both annual and monthly calibration cases described in this work, only a limited number of archetype parameters were assumed unknown and therefore calibrated. Remaining parameters were defined deterministically under the assumption that they were known by the modeler or negligible. As described in Chapter 4, the number of parameters required for calibration in order to capture all model uncertainties, need to be determined in each modeling case through screening and sensitivity analysis.
- The validation exercises in Chapters 4 and 5 showed that it is possible to apply calibrated archetype parameters obtained from a subset of buildings, to characterize other similar structures belonging to the same archetype. However, this only holds true as long as the behavior and demographic characteristics of building occupants are equivalent in both cases. Furthermore, the validation of parameters was performed based on a single sample of between one and three hundred buildings due to limitations in computation time and resources. Smaller or larger sample sizes may be required depending on the archetypes and locations considered.

## 7.2 Research outlook

The research presented in this dissertation has shown that today any municipal government can develop and apply an UBEM simulation infrastructure, relying on data it is already collecting and limited samples of metered energy demands by building. Perhaps more importantly, the proposed archetype calibration methods open the door to new research and application opportunities for urban energy modeling that will enable urban stakeholders to better manage the built environment.

### *7.2.1 Modeling hourly demands*

In this work the application of a calibrated UBEM has only been tested in the evaluation of single demand values at an annual scale. However, the calibration to monthly demands demonstrated in chapter 5, introduced a workflow that can be applied in the analysis of data at smaller temporal scales, and eventually in the calibration of hourly demands. The resulting level of accuracy would radically increase the value of UBEMs for utilities and municipalities alike, since the feasibility of energy supply solutions such as local solar generation or district micro grids, depends largely on the time and size of hourly demand peaks. Regarding solar generation for example, the deployment rate of PV systems in the US has doubled in the last 5 years, and a majority of that growth is due to urban rooftop systems which could cover in the future almost 30% of the national electricity demands [181,182]. While the potential for urban PV is enormous, the temporal mismatch between peak solar production and peak electricity demands throughout a day is a well-known barrier for large scale implementation. Late afternoon or evening peaks in combination with PV can result into the so called daily “duck-curve”, forcing energy providers to respond to unmanageable demand increases in a short amount of time [125]. Similarly, the effective use of energy storage [183] or demand response technologies for the effective management of the electricity grid, requires a detailed understanding of hourly building demands. The capability in UBEMs to estimate how such demands would change in different weather or growth scenarios, will be especially valuable for utilities in their efforts to manage risks, and could result in considerable financial savings. In the opinion of the author, an exciting research opportunity in the UBEM field now opens around this issue.

To achieve the required modeling accuracy, further research needs to be developed in calibration techniques and occupant modeling at the urban scale. The Bayesian approach introduced in this dissertation has been applied for the estimation of a limited number of peak demand parameters, such as occupancy or lighting density, while maintaining the associated 24 hour operation schedules fixed. In addition, calibration at an hourly scale will require estimating the most likely shape of these schedules, by typical weekday and weekend, for every particular occupant type or building use. Given the stochastic nature of occupant behavior and resulting hourly demands, extensive research in the field of BEM has focused on developing modeling techniques that combine occupant data monitoring with probabilistic methods [134,135]. However, their application significantly increases the number of uncertain parameters in a model, rendering calibration unfeasible so far at an urban scale.

The partition of building occupants into types, equivalent to building archetypes, could simplify the procedure and number of parameters, and allow for Bayesian hourly calibration as presented here. For that purpose, UBEM simulations could be combined with statistical clustering methods such as k-means [184] or principal components [185], already successfully implemented in the analysis of use time surveys or metered electricity demands. Alternatively, the use of surrogate statistical models, similar to the one developed in chapter 5, could reduce simulation times enough to allow for the analysis of hourly combinations of parameters. Surrogate modeling has been applied in BEM with a variety of purposes, including design optimization, model calibration and real time building operation analysis [170], and could be easily adapted for urban modeling purposes. Regardless of the calibration and simplification methods available, the most fundamental requirement to achieve hourly accuracy in UBEM is the access to training datasets of hourly metered energy demands. This information is quickly becoming available at a large scale with the increasing use of smart meters, but is also raising accessibility questions regarding information ownership and occupant privacy, which are further discussed in the following section.

### *7.2.2 Big data accessibility for live UBEM*

Throughout this dissertation, it has been made clear that the generation of a useful calibrated UBEM requires gathering and processing large amounts of data regarding buildings, occupants and especially metered energy demands. While this data dependence is unavoidable in any bottom-up energy model, this work has introduced techniques that can reduce requirements and simplify the modeling process. Regarding buildings, the partition of a building stock into archetypes avoids the characterization of each individual structure. Furthermore, the Bayesian calibration of archetype parameters only requires a metered energy data for a limited sample of buildings. The purpose of these and similar methods is to more effectively use the available information, by using the heat transfer principles behind UBEMs to interpret the available data or validate assumptions about building operation.

This capacity for data interpretation, possible through the combination of simulation and statistical techniques, represents an exciting opportunity for municipalities and energy providers, now that "big data" about cities and citizens is becoming increasingly available. In this context, a municipal UBEM can become an infrastructure for the analysis of datasets regarding demographics, real estate values, building certification or energy consumption, which in turn can add detail and accuracy to the model. The most obvious case for big data integration in an UBEM involves the energy use information gathered through "smart metering". Smart meters, or Advanced Metering Infrastructure (AMI) devices, are electricity meters that can measure and record hourly and sub hourly consumption, and establish two way communications between customers and utilities. AMIs have become the standard system in the US, installed in over 50% households since 2016 [8], and offering not only access to demand data but, in select states such as California or Texas, the option through "green button" programs to share this data with third parties with the consent of the customer. In this scenario, the real time access to thousands of hourly building demands could be integrated with a municipal UBEM, potentially allowing for a constant calibration of archetype parameters. This continuously refining model could be later used by municipalities and utilities to model future scenarios or interpret metered data.

Although AMIs are the most relevant source of big data for UBEM, other "smart devices" could also be potentially connected to a municipal building simulation infrastructure. Smart thermostats have been used in research for the study of hourly set point temperature choices, to identify occupant behavior patterns [186]. As such home management technologies become more common, they could also serve as a source of modeling information for the refinement of archetypes. Similarly, GPS data from smart phones has been proposed in research as a big data source for the analysis of urban travel behavior [187]. A similar technique could be used to produce real time schedules by building or archetype, and contribute to the model accuracy. Finally, energy related data sources are not restricted to recording smart devices, and also include national detailed databases about buildings. The growing databases of Energy Performance Certificates (EPCs) compiled in all member countries in the European Union, include information about constructions and systems for large numbers of buildings [94]. Municipal UBEMs could integrate these and similar certification datasets, and contribute in the process of quality assessment of certificates, comparing reported information with archetype parameters and simulation results. These and equivalent opportunities for the productive integration of big data in UBEMs are only going to grow in the near future. Hence, urban modeling research has to focus on developing standardized formats and integration workflows that can allow models to interact with growing datasets, and further calibrate at the detailed urban scales of neighborhoods or blocks. In this effort, the thermal simulation techniques here presented will need to be combined with surrogate building models, statistical analytics and data mining methods.

As promising as the integration of UBEM with big data sources can be, it also raises important questions of privacy and data ownership. As previously discussed in this document, metered energy data is only useful for calibration if it can be associated with specific buildings, or, in the case of smart meters, to specific owners. Currently, due mainly to privacy concerns, energy data is rarely accessible to modelers and municipalities unless it is aggregated or anonymized. However, the situation is changing with the introduction of data sharing programs with customer consent, such as "green button", which will in the future change the paradigm of energy data ownership. The question of data privacy and ownership is of course not exclusive to the energy field, and similar barriers for data research and modeling exist for example in the case of health records. It is the opinion of the author that the use of building and energy data exclusively for the characterization of archetype parameters within a municipality can mitigate most privacy risks and contribute to the accuracy and relevance of UBEMs. In any case, a strong collaboration is necessary between municipal governments and utilities to address these accessibility limitations.

### *7.2.3 Building performance regulation and compliance*

With an urban design case study in Boston in chapter 6, this work has hinted to the possibility of using calibrated UBEM archetypes as a baseline for evaluating new urban developments. This type of application opens the door for a full reconceptualization about the way municipal governments regulate building energy performance. Currently, most cities in the US or the EU have in place energy efficiency requirements for buildings, which either translate national or state energy codes directly, or encourage the use of third party certification schemes such as LEED [47]. In the case of Boston for example, all new construction is required to comply with the Massachusetts Stretch Code [188], which in turn requires a 10% energy use reduction over compliance requirement of ASHRAE Standard 90.1 Appendix G [45]. Alternative local rules might require a certain EnergyStar score as described in the Boston example. Additionally, Boston also requires new buildings to address other sustainability requirements, by following the checklist provided by LEED and proving that the project would be "certifiable" [189]. Although these and similar approaches tied to energy codes are fundamental in the general improvement of the built environment, and contribute to the reduction of energy related emissions, they are somehow generic and agnostic to the conditions and plans for a specific neighborhood or district. With access to a municipal calibrated UBEM and the associated library of building and occupant information, city governments can potentially write compliance requirements by block or district, based on their simulated baseline model. Furthermore they can require new urban developments to demonstrate the fulfillment of such requirements by using the same stochastic input parameters that the city has defined for the area. UBEM enables urban planners to engage the building stock with a completely new level of spatial resolution, and effectively develop performance based energy zoning.

New and exciting research in the fields of energy modeling and urban planning can be now developed, to identify the metrics and regulation approaches appropriate to different scales and purposes. For example, in the planning of a new district system combining cogeneration of heating and cooling, solar PV deployments and batteries, a city will have to collaborate with the local utility to characterize what hourly demand profiles the system will be able to cope with. Using an UBEM, an urban planning department can require a new building coming in the area to demonstrate, using the municipal baseline archetypes that it stays within the acceptable demand limits. The work developed by MIT Lincoln Labs in the prioritization of micro grid locations in Boston based on the results of this thesis [174], already introduces techniques evaluate how adding new buildings to a local system would affect its performance. In a similar approach, UBEM calibrated archetypes can be provided to design teams in the context of a master-plan or urban design competition. Using them as a baseline, a design team would be required to achieve certain performance goals, that later could be checked by the municipal planning department when comparing different proposals. A similar application of UBEMs has been proposed in research for the analysis of 14 competitions proposals for a city quarter in Munich in terms of energy demand and solar generation potential [173]. The availability of a library of urban calibrated archetypes in a standardized format such as the TLF proposed in chapter 3, will enable these applications, as well as offer detailed information about the built environment to a larger audience, including technology companies, real estate developers and investors, and building users in general.

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## Publications written in the context of this dissertation


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## Abbreviations

| | |
|---|---|
| GHG | Greenhouse Gases |
| UBEM | Urban Building Energy Model |
| BEM | Building Energy Model |
| BPS | Building Performance Simulation |
| GIS | Geographic Information Systems |
| LIDAR | Light Detection and Ranging |
| ASHRAE | American Society of Heating Refrigerating and Air Conditioning Engineers |
| IBPSA | International Building Performance Simulation Agency |
| LEED | Leadership in Energy and Environmental Design |
| USGBC | United States Green Building Council |
| BREEAM | Building Research Establishment Environmental Assessment Method |
| GUI | Graphic User Interface |
| CAD | Computer Aided Design |
| AIA | American Institute of Architects |
| TMY | Typical Meteorological Year |
| UHI | Urban Heat Island |
| IPCC | Intergovernmental Panel on Climate Change |
| BPDA | Boston Planning and Development Authority |
| WWR | Window to Wall Ratio |
| HVAC | Heating Ventilation and Air Conditioning |
| CBECS | Commercial Buildings Energy Consumption Survey |
| RBECS | Residential Buildings Energy Consumption Survey |
| EPC | Energy Performance Certificate |
| BIM | Building Information Modeling |
| EUI | Energy Use Intensity |
| BERDO | Building Energy Reporting and Disclosure Ordinance |
| TLF | Template Library File |
| XML | Extensible Markup Language |
| JSON | JavaScript Object Notation |
| CHP | Combined Heat Power |
| KISR | Kuwait Institute of Scientific Research |
| KU | Kuwait University |
| COP | Coefficient Of Performance |
| LHC | Latin Hyper Cube |
| KS | Kolmogorov Smirnov test |
| PBT | Pay Back Time |
| FAR | Floor Area Ratio |
| LOR | Land Occupancy Ratio |