URBAN BUILDING ENERGY MODELING AS A DYNAMIC TOOL FOR SUSTAINABILITY PLANNING

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Submitted to the Department of Urban Studies and Planning
In partial fulfillment of the requirements for the degree of

Master in City Planning

at the
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Abstract
Cities around the world are actively aiming to reduce greenhouse gas emissions in an effort to combat the negative consequences associated with anthropogenic climate change. The City of Boston is no exception—in 2011, then-mayor Tom Menino established the rigorous goals of reducing city-wide greenhouse gas emissions by 25% by 2020 and by 80% below 2005 levels by 2050. Given the realities of finite time and resources, it’s critical to identify the most effective strategies to achieving energy efficiency in order to meet these objectives.

This thesis explores how urban building energy modeling (UBEM) can be utilized to develop high-impact community-led energy efficiency programs. UBEM is a recently developed type of bottom-up energy modeling that presents a number of advantages over past urban energy modeling methods—namely, the ability for comparing complex scenarios, and the ability to generate hourly load profiles for individuals buildings. In addition, literature suggests that community-based energy efficiency programs achieve higher participation rates than traditional information-based programs. This thesis combines the technical benefits of UBEM with the practical advantages of community-led energy efficiency programs to develop a context-specific and community-based energy efficiency program for the Dudley Triangle neighborhood of Boston. It then explores how this type of a program can achieve the triple bottom line objectives of creating high quality local jobs, reducing environmental impacts, and supporting a local economy.

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This research has been an honor to participate in and I see it as just the beginning of an exciting and fruitful intersection between disciplines. I hope others will be able to carry the torch forward in future years, and I look forward to seeing what comes next.
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Introduction

Cities around the world are realizing the urgency of climate change’s potential threats to humanity like never before. Many are taking an active approach to mitigating climate change with bold climate change plans and greenhouse gas reduction goals. The City of Boston is aiming to reduce greenhouse gas emissions by 25% below 2005 levels by 2020 and by 80% below 2005 levels by 2050 (Boston’s Climate Plan, n.d.). As Mayor Marty Walsh announced in 2014, “There is no issue more urgent than climate action.” (Mayor Walsh Launches Regional Climate Preparedness Effort, 2014)

A critical part of any strategy to reduce municipal energy consumption and greenhouse gas emissions is to improve the energy efficiency of the existing building portfolio. The City of Boston is composed of roughly 92,000 buildings, 90% of which are residential. Working with a broad population of stakeholders to upgrade these buildings to higher standards of efficiency—including the many landlords, tenants, and homeowners throughout the city—will require a significant amount of manpower. Together, the opportunity for energy efficiency improvements and the demand for jobs presents an opportunity to develop a green economy that leads to a more resilient and sustainable city. These efforts also allow for an exploration of triple bottom line metrics that incorporate social and ecological consequences in addition to traditional financial goals.

Another trend has been growing in recent years that meshes well with the objectives outlined above. The Internet is revolutionizing every aspect of our lives—from how we socialize, shop, work, and make decisions—and an extraordinary amount of data is being created in the process. Big Data—defined in a 2014 White House Report on the subject as “the growing technological ability to capture, aggregate, and process an ever-greater volume, velocity, and variety of data”—presents an unprecedented opportunity to better understand the world we live in. (Podesta, Pritzker, Moniz, Holdren, & Zients, 2014). This is turn is driving a paradigm shift in how decisions are made. Suddenly, data exists to inform decisions in a manner that was previously unfathomable. In recent years, shifts in municipal decision making can be witnessed responding to this trend. A prime example is the Cityscore application in Boston, a real-time dashboard that presents key metrics on the city’s performance on a variety of critical topic areas to the Mayor’s office, who respond with programs and policies accordingly. (Cityscore 2016, n.d.). This dynamic type of feedback in policy and programmatic decision making has the potential to spur a new era in civic life.

The ability of technology and data to inform decision making has key implications for greenhouse gas reduction efforts. Given the real-world constraints of time and a fixed budget, municipalities must prioritize certain energy conservation strategies over others. To assist with this decision making process, urban models have been developed to help understand energy consumption on an urban scale. While

1For the purposes of this study, the following definitions are utilized: A green economy refers to economic activities that are related to reducing energy consumption in buildings and transportation, and developing renewable energy sources. Resilience refers to the capacity to withstand and overcome natural disasters and economic fluctuations. Sustainability is the ability for a process or system to endure over an extended time period due to a balance of production and consumption of labor and resources, in the context of ecological, financial, and social environments.
Urban models have been around for a number of years, traditional models have significant limitations regarding the granularity of data and the ability for scenario comparison. Recently, a new form of bottom-up modeling called Urban Building Energy Modeling (UBEM) aims to address these shortcomings. UBEMs apply simulation methods to represent individual buildings as dynamic thermal models, based on the same heat transfer equations and principles that govern individual building energy models. Since UBEMs are based on the same modeling of physical phenomena as building energy models, they can support complex scenario development, including the combination of new technologies and modified occupant behavior (Cerezo Davila, Reinhart, & Bemis, 2016). This is the most useful approach for exploring the impacts of energy efficiency measures and informing stakeholder decision making available to date, and is therefore utilized in this study.

In August 2015, the MIT Sustainable Design Lab completed a seminal project with the City of Boston in which a comprehensive urban energy model was constructed. The study explored the use of readily available data sets in order to create the urban model, with a focus on replicability by other cities. Hourly energy consumption predictions by load type were produced for over 92,000 buildings across the city. Once the model was complete, it was utilized to explore the impact of rooftop photovoltaic panels to offset peak summer energy demands (Cerezo Davila, Reinhart, & Bemis, 2016). This study was the first of its kind and represents a major milestone in urban energy modeling. Now that a comprehensive energy model of the city of Boston exists, it raises interesting questions about how the data can be applied to real-world decision making processes. Specifically, how can this tool be used to inform planning policies and activities? And how can it be used by neighborhood organizations or municipal governments to think strategically about the future? Finally, can it enable entire communities to see how they are interconnected, and illustrate the potential power of collective action?

This study answers some of those questions. While the initial Boston model spanned the whole city and incorporated 13 types of buildings categorized by programmatic use and building vintage (for a total of 52 archetypes), this study explores the impacts of various energy conservation measures (ECMs) on residential buildings in a single neighborhood in Boston. This scenario-based modeling effort demonstrates options to decision makers and will help inform decisions based on affordability, energy savings, and likelihood of implementation. The Dudley Triangle neighborhood in Boston was chosen as the study area due to the proximity of the Dudley Square Neighborhood Initiative (DSNI), an anchor institution in the neighborhood with a strong organizational capacity and history in Boston. DSNI is a non-profit community organization focused on the Dudley Street neighborhood in Boston with a history of grassroots organizing. By working with an established community organization with demonstrated leadership and capacity, this study can inform how energy conservation measures are explored on the neighborhood level. Three key research questions were established to guide this study, as follows:

1. How can an energy model be used to create “what-if” scenarios that allow for a comparison of neighborhood-scale energy conservation programs?
2. How can the “what-if” scenarios account for time?
3. How can census data and demographics be utilized to identify plausible adoption rates and guide policy and programmatic decisions?

The rest of this thesis is structured as follows: Section 2 outlines the critical literature on past programs, key implementation barriers, and the guiding theoretical framework. Section 3 presents the methodology utilized to construct the neighborhood energy model scenarios, and the analytical framework used to perform the analysis. Section 4 reports the results of the simulations, which are discussed in depth in Section 5. Next, an action plan for the Dudley Triangle neighborhood is outlined based on the study’s results. Finally, Section 7 concludes with a number of closing remarks. As this thesis is the jumping off...

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2 Bottom-up modeling refers to data that originates at the building level and is then aggregated on an urban scale (as opposed to top-down modeling, which starts with urban-level data).
point for a significant quantity of further inquiry, opportunities for further research are also briefly discussed.

Background

Boston Energy Efficiency Programs to Date

A review of public documents suggests that energy efficiency and renewable energy projects are not a new focus for the City of Boston. As a coastal city with an acute awareness of the vulnerabilities presented by climate change, the city has been proactive to quantify and mitigate the risks in recent years. In 2007, then-mayor of Boston Thomas Menino enacted an executive order on climate action that required City offices to incorporate climate change into all municipal and community planning, projects, permitting, and review processes (Spector & Bamberger, 2013). In 2009, Mayor Menino created the Renew Boston Initiative to encourage the implementation of energy efficiency and renewable energy projects in Boston’s building portfolio (Swing, 2013). In 2007, Boston set a greenhouse-gas reduction goal of 25% below 2005 levels by 2020 and 80% below 2005 levels by 2050 for municipal buildings. In 2011, these goals were extended to include the whole city (Greenovate Boston 2014 Climate Action Plan Update). These overarching goals provide the framework for energy efficiency efforts in Boston, and demonstrate that there is significant political will to support these types of projects.

While both Renew Boston and the city’s climate change goals are broad-reaching, specific attention is paid to the residential sector. In the first phase of the Renew Boston program, $200,000 was spent to provide over 160 residents with comprehensive energy efficiency services. Phase 2 of the Renew Program involved $2 million in Energy Efficiency and Conservation Block Grant funding to provide no-cost weatherizations to 1750 residents, and $1.1 million was spent on six multi-family energy efficiency projects. Further city funds were procured to provide 2260 additional no-cost insulation projects. In addition, a municipal energy office was established with a small team of permanent staff to further support city-wide efforts (Swing, 2013).

In addition to programs specific to the city of Boston, state programs have been a critical part of energy efficiency efforts to date. Two programs in particular have played a significant role in implementing energy efficiency projects in Massachusetts. The first is Mass Save, an initiative sponsored by Massachusetts gas and electric utilities and energy efficiency services (Mass Save, 2016). The program provides no-cost home energy assessment for MA residents, and a number of rebates and incentives on energy efficiency measures, such as weatherization rebates of 75% up to $2000, rebates on energy-efficient heating and hot water heating equipment, and 0% financing on home loans for energy efficiency projects. Second, the Massachusetts Green Communities Program—enacted by the Green Communities Act of 2008—has also provided critical support for energy efficiency efforts in Boston. The Green Communities Provides technical assistance and a stream of grant funding for cities and towns and MA that adhere to specific guidelines deeming them a “green community”.

Finally, Boston received a significant amount of financial support through the federal American Recovery and Reinvestment Act. Boston was awarded an Energy Efficiency Community Block Grant that provided $2 million for 1750 residents to receive no cost weatherization. In addition, over $1 million of EECBG funding was used to complete six low-income multi-family energy efficiency projects (Swing, 2013). As a result of the many efforts listed above, the American Council for an Energy-Efficient Economy (ACEEE) lists Massachusetts as the top-ranked state in the nation—and Boston as the top-ranked city—for policies and programs that encourage energy efficiency and renewable energy (Massachusetts, 2015).
The Community-Based Model

Despite the breadth and depth of Boston’s energy efficiency and renewable energy programs to date, there are still major challenges to reaching broad implementation across the residential building portfolio. In 2013, four years after the launch of the Renew Boston Program, only 2% of 2-3 family dwellings had been recently insulated—a key strategy for improving building energy efficiency (Swing, 2013). This suggests that more needs to be done to achieve higher implementation levels across the city. The community-based approach offers one strategy towards addressing this implementation gap. A community-based approach leverages the credibility of an existing community organization or institution, its familiarity with the target group, and its contacts in the community. Two community-based energy efficiency programs of note have taken place in Massachusetts—the Marshfield Energy Challenge in Marshfield, Massachusetts that ran from spring 2008 to fall 2009, and the Community Mobilization Initiative in New Bedford, Massachusetts which ran from summer 2010 through spring 2011 (Brandt, 2011). The Marshfield program achieved a participation rate of 10% in its first year, and a quarter of the retrofits completed involved insulation and weatherizations (Michaels, 2009). In New Bedford, 21.8% of households contacted received an energy audit (Brandt, 2011). These programs suggest that the community-based strategy is a promising alternative to traditional outreach methods, which rely on a passive dissemination of information.

The results from the Marshfield and New Bedford programs are supported by other research on the topic. In *Utility Demand-Side Management Experience and Potential – A Critical Review*” (Nadel, Pye, & Jordan, 1994), the authors found that community-based programs achieved the highest participation rates among comprehensive weatherization programs (Nadel, Pye, & Jordan, 1994). Two programs in particular were extremely successful: the Hood River Conservation Project in Hood River, Oregon and the Espanola Power Savers Project in Espanola, Ontario. Both programs achieved participation rates of over 85% across a 1.5 to 3 year period. The two programs employed a strategic approach that targeted every home in a single community, and installed measures at no cost to the consumer. Both programs also involved extensive community-based marketing that combined informational mailings and newsletters, local media coverage, visible signage in the community, promotion at local events, and more (Nadel, Pye, & Jordan, 1994). These studies illustrate how a targeted community-based program with a comprehensive outreach approach can achieve significant adoption rates of residential energy-efficiency measures. They also demonstrate that overcoming key barriers—including cost and information—are critical to achieving broad program participation.

The shift towards community-based approaches is based on a number of factors. In “Enabling Deep and Scalable Energy Efficiency in Communities”, three key reasons are provided: collective action is needed in order to meet our energy reduction goals, communities are enthusiastic about a community-based approach, and utilities and communities can support each other’s energy efficiency needs (Michaels, 2009). Furthermore, the community-based approach is gaining momentum due to their focus on local context and community involvement. Lawrence Berkeley Laboratory suggests that in the future, “effective programs will tend to be tailored to the location, thoughtfully researched and piloted, personalized to the target audience, and more labor-intensive than simple incentive programs” (Fuller, et al., 2010). Finally, by working with local partners, community-based programs can gain community buy-in, which is critical to the broad adoption of energy efficiency measures.

Based on this research, a partnership was established with the Dudley Street Neighborhood Initiative so that a community-based approach could be explored as part of this study. DSNI was chosen as a partner due to its history of community organization and organizational leadership. The Dudley Street Neighborhood Initiative was established in 1984 by residents in and around the Dudley Street area, a community in the Roxbury neighborhood of Boston. The area had been the site of significant disinvestment and decline, and by 1984, nearly one-third of the land in the Dudley Street area was vacant.
In response, the community organized in an effort to revitalize their neighborhood and prevent the loss of land to outside speculation. In 1988, after four years of effort and activism, DSNI was granted eminent domain over abandoned properties within its boundaries—the first achievement of this type for any community-based nonprofit in the country (Organizational History).

Since 1988, DSNI has continued to work on community revitalization efforts. The organization orients its efforts around its mission of “empowering Dudley residents to organize, plan for, create and control a vibrant, diverse, and high quality neighborhood in collaboration with community partners”. DSNI’s approach to neighborhood revitalization involves economic, human, social, and physical development. Today, the organization boasts 3,000 members that serve a neighborhood community of approximately 24,000 residents. Currently, the organization focuses on three strategic areas: community economic development, resident leadership, and youth opportunities and development (DSNI Overview). The grassroots history of the community and their current focus areas make DSNI a natural choice for innovative energy projects that lead to a resilient community and foster a local green economy.

**Literature Review**

**From Bottom Line to Triple Bottom Line**

In the 1990’s, in an attempt to quantify the success of a business beyond the traditional financial “bottom line”, business author and entrepreneur John Elkington developed the idea of the triple bottom line (Slaper & Hall, 2011). This effort grew out of the social and corporate responsibility movement and provided a new framework for conceptualizing the success of a business that incorporated ecological and social benefits. The triple bottom line is usually defined as social-ecological-financial, sometimes called “People, Planet, Profits.” By considering the social, ecological, and financial implications of business decisions and aiming to satisfy goals in each focus area, governments, institutions, and organizations essentially have a new way for conceptualizing and measuring sustainability.

Today, as the climate warms and the negative consequences of resource depletion and pollution become more apparent, the triple bottom line accounting framework is gaining traction across business, industry, and government sectors. Some organizations utilize triple bottom line accounting explicitly, while other organizations are simply influenced by the ideas and values behind it. The Green Solution echoes the triple bottom line ideology by arguing for energy efficiency improvements to buildings which would save money (financial goals), create jobs (social goals), and reduce the environmental impact of buildings (ecological goals). Similarly, the Renew Boston Plan cites the intention to create a “greener, healthier, and more prosperous city” (Swing, 2013). In recent years, other authors in the realm of organizational management have further refined ideas related to the triple bottom line framework in order to better understand and instruct business on how to position themselves for long-term success. In Leading from the Emerging Future- From Ego-System to Eco-System Economies, Otto Scharmer and Katrin Kaeufer conceptualize the ideas of triple bottom line as a decision making framework that is as relevant for individuals as it is to global institutions. While their framework varies slightly from the original triple bottom line idea, and is a jumping off point for a more in depth exploration of economic logic and corporate decision making, the underlying ideas are consistent. Ultimately, the process they describe allows for a multifaceted, holistic understanding of the comprehensive impact of one’s actions. The process they describe allows for decision making that is open-minded, creative, and ready to handle the complex challenges of the future in a viable, sustainable, and meaningful way.

As triple bottom line ideas and metrics continue to grow and develop, case studies of successful demonstrations of this type of accounting framework abound. For instance, the Global Alliance for Banking on Values (GABV), an independent network of banks and banking cooperatives was established in 2009 with a shared mission of using finance to deliver sustainable economic, social, and environmental development. Seven years after its creation, GABV boasts 28 financial institutions across six continents serving 20 million customers (About Us, 2016). In Cleveland, Ohio, the Evergreen Cooperative Initiative
is working to create high-quality, living-wage jobs in six low-income neighborhoods (About Us, 2016). Renewable energy has provided one of the pathways to achieving this objective—since 2009, Evergreen Energy Solutions has been the regional leader in solar power installations. Case studies like these have demonstrated that achieving social, ecological and financial goals is feasible, and helped to inspire this study.

Likewise, a triple-bottom line framework provided a powerful argument for the Green Justice Coalition’s 2008 report *The Green Justice Solution: A Win-win Plan to Prevent Climate Crisis and Jumpstart an Equitable and Sustainable Economic Recovery*. The Green Justice Coalition is a partnership of labor unions, environmental organizations, community groups, and other allied organizations in support of a sustainable, equitable, and clean energy economy in the Boston area. Their seminal report called for a transformation of the economy to support green jobs—such as those focused on upgrading homes to be more energy efficient—while addressing issues of equity and environmental sustainability in the process. It articulates twelve compelling reasons to expand energy efficiency retrofits of existing buildings in Boston, including saving money for consumers, a high return on investment, keeping money in the local economy, and improving air quality (Connelly, 2008).

The Green Justice Solution makes a compelling case for energy efficiency retrofits as a key mechanism towards creating high quality “green-collar” jobs. In the context of this thesis, green-collar jobs are considered those that are focused on energy efficiency or renewable energy services, including energy audits, retrofitting insulation, and more. Additionally, these roles provide a high quality work environment for employees. Green-collar jobs typically require additional training beyond the traditional trades, resulting in higher skilled work. As such, green-collar work provides safe, healthy work environments, fair wages and benefits, and allow for professional growth. According to the report, every $1 million invested in residential energy efficiency retrofits creates 11 on-site jobs and up to 5 indirect support jobs. These types of investments also indirectly support manufacturing of energy efficiency products (Connelly, 2008). These facts underscore the argument that energy efficiency and renewable energy projects present an opportunity to create jobs, reduce unemployment, and reduce economic inequality, while ensuring that Boston is prepared to meet the needs of the future.

**Adoption Rates**

While it is critical to understand the total potential energy reduction that a given energy-efficiency technology can result in, it is equally important to understand how quickly a given technology can and will be adopted. Given finite resources and time, the rate of implementation of a given energy efficiency technology is pivotal to the success of an energy efficiency program. It is of particular importance in the context of residential energy efficiency measures because of the dispersed stakeholders with diverse socioeconomic status, values, communication channels, and priorities. Fortunately, technology adoption has been the subject of a vast body of literature, which can provide valuable insight into understanding how quickly and why a technology is adopted—and what factors can influence these variables.

Technology diffusion refers to the manner in which a new technology spreads through a target audience of potential adopters. The literature on technology diffusion suggests that the adoption curve is generally S-shaped, with slow adoption rates at first, followed by a period of rapid adoption, and finally a deceleration in adoption rates as market saturation is achieved (Barreto & Kemp, 2007). Furthermore, technology diffusion has a distinct spatial pattern as well, with rapid adoption in centers and slower adoption rates at the periphery. The diffusion process at the periphery “starts later but is normally faster” (Barreto & Kemp, 2007). A number of technology diffusion models have been developed to explain these trends, which are discussed in the following paragraphs.
Models of technology diffusion

One of the most well-known models of technology diffusion is the epidemic model, named for its historic use in characterizing the spread of disease among a population. In this model, the rate of infection is proportional to the number of infected individuals. In other words, the greater the number of infected individuals, the greater the likelihood of infection. In terms of energy efficiency measures, the spread of information through communication channels and social networks, or information contagion, follows a similar pattern. The epidemic model provides a fruitful starting point for understanding the S-shaped curve of technology diffusion among a population, however it has a key limitation. This model assumes that all members of a population are equally likely to contract a disease (or in this case, adopt a new technology), whereas in reality significant intra-group differences exist that play a factor in determining when and by whom a technology is adopted. (Cantono & Silverberg, 2009).

A contrasting explanation of technology diffusion is found in the rank effects model, which explores intra-group differences, or agent heterogeneity, and the effects they have on decision making. Originally developed to describe the likelihood of firms adopting a new technology, it is equally applicable to individuals. The model suggests that firms adopt new technology based on factors such as firm size, age, capital ownership, liquidity, quality accreditations, management techniques, and more (Battisti, 2008). These factors are combined into a ranking system that describes the overall benefits of adopting the new technology for each firm. Firms that rank the new technology highly will adopt it first, while firms which attribute a lower ranking to a given innovation will adopt it later or not at all. In the context of households considering energy efficiency measures, a similar ranking may be constructed on parameters such as cost, visibility, compatibility with existing environment, and more. While this model effectively accounts for intra-group differences, it fails to account for inter-group relationships and the significance of communication channels described by the epidemic model (Cantono & Silverberg, 2009).

The percolation model begins to combine the epidemic and Probit models to provide a more nuanced understanding of technology adoption based on two primary factors—the decisions of one’s neighbors to adopt a technology, and the price of the new technology. According to the percolation model, a consumer will consider purchasing a product only if it has already been bought by one of his or her neighbors. If this condition is fulfilled, the consumer will purchase the product if it is below the price he or she is willing to pay (Cantono & Silverberg, 2009). In this case, an individual’s willingness to pay can be used as a proxy for the rankings described by the Probit model. The model also introduces probability equations to describe how a technology diffuses. It also importantly suggests that that there may be a price threshold that a given technology must fall below in order for widespread adoption to take off.

These models present three important takeaways for the diffusion of energy efficiency technologies. First, social networks and communication channels play a significant role in spreading information, demonstrating a new technology’s compatibility with existing environments, and shaping social norms. Second, it’s clear that intra-group differences may cause certain segments of a population to adopt a new technology before other population segments. Finally, there may be a price threshold that a given technology must fall below in order to achieve widespread adoption. By considering these factors when designing policies and programs to encourage technology adoption, more effective outcomes can be achieved.
As the Probit and percolation models indicate, not all potential adopters adopt a new technology at the same time. What, then, motivates some to adopt early, and others not to adopt at all? To address this question, five main classifications of a population have been developed to describe the various levels of receptiveness to adopting a new technology (Table 1).

<table>
<thead>
<tr>
<th>Adopter Category</th>
<th>% Adopters</th>
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<tr>
<td>Innovators</td>
<td>2.5</td>
</tr>
<tr>
<td>Early Adopters</td>
<td>13.5</td>
</tr>
<tr>
<td>Early Majority</td>
<td>34</td>
</tr>
<tr>
<td>Late Majority</td>
<td>34</td>
</tr>
<tr>
<td>Laggards</td>
<td>16</td>
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Table 1: Adopter Categories. Adopted from Mahajan, 1990.

The five categories of adopters are composed of individuals that differ based on socioeconomic status, personality values and communication behavior (Diaz-Rainey & Ashton, 2015). This importantly suggests that when exploring the propensity for the adoption of energy-efficiency measures, demographics and income matter. For instance, Innovators tend to be from higher social status groups, have had more education, and tend to be rational, display greater empathy and have greater social interaction as compared with the Laggards (Diaz-Rainey & Ashton, 2015). Furthermore, the more visible an energy-efficiency technology is, the more responsive it is to the influences of social networks. This means that all else equal, more visible technologies will have higher diffusion levels than less visible technologies (Diaz-Rainey & Ashton, 2015).

There are also variations in the primary motivations for adopting an energy efficiency technology. Primary motivations for adoption range from saving money, saving energy, or improving thermal comfort to protecting the natural environment. These motivations vary by the adopter characteristics (e.g. age, socioeconomic status, demographics, etc). For instance, Early Adopters are more likely to come from higher socioeconomic groups and therefore are more carefree about energy use. As a result, they are driven to adopt energy efficiency measures more by environmental concerns than by a motivation to save...
money. On the contrary, the elderly are driven by a desire to save energy. Furthermore, late adopters of technologies tend to be renters rather than owners. The importance of adopter characteristics in determining the likelihood and timing of adoptions has critical implications for programs and policies designed to encourage the adoption of energy efficiency technologies (Diaz-Rainey & Ashton, 2015).

Methodology

The evaluation of residential ECMs using an UBEM approach involved five main steps (Figure 4). First, a baseline energy model of the existing buildings was constructed using the approach described by Cerezo Davila et al (Cerezo Davila, Reinhart, & Bemis, 2016). Second, the key energy conservation measures applicable to the types of buildings present in the neighborhood were identified, the impacts on building systems assessed, and a set of building archetypes which reflected current and future conditions was developed. Simulations were then run and consumption data obtained. Next, census data and tax assessor data were utilized to correlate the results to the demographics of the neighborhood. Finally, implementation strategies are explored based on a review of financial mechanisms available to Dudley Triangle residents. These key steps are described in the paragraphs below.
Part 1: Building the Baseline Urban Energy Model

I.a. Model Characterization

The Dudley Triangle neighborhood boundary—as defined by DSNI—formed the bounds of the study area for the purposes of this thesis (see Figure 5). This decision was made in order to establish continuity with past efforts in the neighborhood, which utilized the same boundary to represent the neighborhood extents. In addition, the scale worked well for the modeling tasks desired. With over 400 buildings in the study area, the scope was broad enough to justify the use of UBEM (which is intended for urban scales), while small enough that the actual modeling tasks were feasible given the time constraints of the project. The limited scope of this study reduced the time necessary to generate the urban models, thus allowing for the creation of more detailed building archetypes and a comparison of “what-if” scenarios. In contrast, the city-wide model of Boston completed by the Sustainable Design Lab in 2015 encompassed over 92,000 buildings and took months to complete (Cerezo Davila, Reinhart, & Bemis, 2016).

Three basic inputs are required in order to develop an UBEM: local weather data, building geometries, and building construction and usage data. (Cerezo Davila, Reinhart, & Bemis, 2016). Typical Meteorological Year (TMY) weather data from Boston Logan Airport weather station provided the local weather information for this model. The remaining two inputs required substantially more data manipulation and assumptions. This process is the subject of the sections below.

Step 1: Develop 3D Model

The first step in building the Dudley Triangle UBEM was to create a 3D model of the buildings in the study neighborhood. Geographic Information Systems (GIS) databases obtained from the City of Boston provided many of the needed parameters for each building in the study area, including the footprints,
number of stories, roof elevation, and ground elevation. To approximate the 3D geometry of each building, the GIS shapefile containing the building footprints was imported into the Rhinoceros 3D CAD environment and each building was extruded based on its roof elevation (McNeel, 2015). While this approach is somewhat simplistic—assuming a flat roof for every building, and ignoring variations in elevation in a single building—it provides a viable method for approximating the built environment for the purposes of an energy model, in which simplified geometries are preferable (Cerezo Davila, Reinhart, & Bemis, 2016).

Step 2: Categorize Buildings

Four hundred and thirty five residential buildings were identified within the study area using FY14 Tax Assessment data provided by the City of Boston. To represent these buildings, a series of archetypes, or representative depictions of the buildings in the Dudley Triangle area, needed to be developed. Archetypes consist of a set of geometric properties that characterize a building’s thermal performance—such as the efficiency of the heating and cooling system, the plug loads\(^3\), the thermal resistance of the walls, and more. Archetype generation consists of two steps: segmentation, or the grouping of buildings with similar properties, and characterization, or the definition of the complete set of thermal properties for each archetype (Cerezo Davila, Reinhart, & Bemis, 2016). The buildings in the Dudley Triangle area were segmented based on two key parameters: first, the number of units per floor (or “occupant density”), and second, the year of construction (or “vintage”). Occupant density is an important factor in determining a building’s plug loads and internal heat gains\(^4\), while a building’s vintage informs assumptions about construction methods and materials and the age and style of appliances. The construction methods and materials effect the thermal resistance and airtightness of the building envelope, while the ages and styles of appliances contribute to the internal heat gains.

In order to classify the buildings by these two parameters, property information was obtained from FY14 City of Boston Tax Assessment Data. The dataset listed three key metrics that were used to identify the number of units per floor for each building: the total number of units, the total number of kitchens, and the number of floors. For the most part, the number of units per floor were readily calculated from these three variables. In the few cases where inconsistencies arose, the number of units per floor was determined using a combination of Tax Assessor data, GIS, and Google Maps. More details on the assumptions utilized in this step can be found in Appendix___.

Once the number of units per floor was identified, each building was classified accordingly. Eight variations in occupant density were identified in the area (Figure 7). These density classifications were then further divided based on vintage (also listed in the FY14 Tax Assessor data). For simplicity’s sake, four key time periods were chosen: Pre-1950, 1950-1980, 1981-2000, and 2001-Present. These time periods were chosen based on major changes to building codes, under the assumption that construction methods generally adhere to building codes, and that construction methods change when building codes are modified. When the eight occupant density classifications were combined with the four temporal categories, a total of 32 building classifications emerged. These thirty-two classifications captured the major variations across the residential buildings in the Dudley Triangle and were used as the basis for the neighborhoods archetypes.

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\(^3\) Plug load refers to the energy used by products or appliances that are powered by means of an ordinary AC plug, such as a coffee maker, hair dryer, window air conditioner, or personal computer. This term is usually used in contrast to other types of energy uses like lighting, heating, ventilation, and central air conditioning.

\(^4\) Internal heat gain refers to the sensible and latent heat generated by occupants, lighting, and appliances within a building.
Step 3: Define Occupant Behaviors

Next, an evaluation of what appliances were being used, and when, was performed. These factors, known as "loads" and "schedules" in UBEM, describe how building systems operate on a daily basis. Often, broad generalizations are made regarding the behavior of building occupants, since there is little data available to more accurately describe who is using a building, when, and how. However, these generalizations are often oversimplifications of human behavior. Naturally, not everyone in a given
geographic area wakes up at the same time, cooks at the same time, turns on their air-conditioning at the same time, and so forth. Nevertheless, these generalizations provide an important starting point to understanding the impacts of human behavior on building energy consumption.

In the city-wide urban building energy model of Boston completed by the Sustainable Design Lab in 2015, all residential buildings were assumed to have the same loads and schedules—collectively referred to as a “user profile”. However, since this study focused exclusively on residential buildings, a more granular understanding of neighborhood demographics, and their impact on building energy consumption, was desired. Therefore, four basic user profiles were developed to describe different types of households. Next, assumptions were made about the associated characteristics of each household type (Table 2)\(^5\). These characteristics were then used to calculate the equipment and lighting loads and schedules in each residence using a spreadsheet method that assumed a basic number of lightbulbs and appliances per space type\(^6\). When each of these four user profiles were combined with the 32 building archetypes, a total of 128 baseline scenarios emerged.

<table>
<thead>
<tr>
<th>User Profile</th>
<th>Typical Characteristics</th>
<th>Key Demographic Identifier</th>
<th>Census Table(s) Utilized</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elderly Couples</td>
<td>Older appliances, bed early, lower equipment density</td>
<td>Adults over 65</td>
<td>T007</td>
</tr>
<tr>
<td>Families</td>
<td>Parents work 9-5, medium appliance density. Highest equipment loads.</td>
<td>Households with one or more individuals under age 18</td>
<td>T018</td>
</tr>
<tr>
<td>Young Professionals</td>
<td>Stay up late, up early, high density occupancy</td>
<td>Population age 18-24</td>
<td>T007, T017, T018, T021</td>
</tr>
<tr>
<td>Students</td>
<td>Stay up latest, sleep late, highest density occupancy</td>
<td>Non family households – student households + family households without kids – elderly couples</td>
<td>T007, T021</td>
</tr>
</tbody>
</table>

**Table 2: User profiles with assumptions about associated behavior**

**Step 4: Develop Building Templates**

A total of 52 fields outlined in an XML template provide the basic thermal properties of each of the 128 scenarios. The information listed in each XML template includes the thermal properties of all envelope surfaces and glazing, internal peak loads for equipment and lighting use, the efficiency of the heating and cooling systems, etc. Ideally, statistical data from the investigated building stock would be used to set these parameters for each scenario. However, this data was not readily available throughout the duration of this study. In the absence of such data, published standards and hand calculations based on the thirty-two building classifications and the four user profiles were used to populate these fields. For instance, building codes from the pre-1950 period required less insulation than is required today—resulting in higher infiltration rates. The templates created for this period reflect this, with an infiltration rate of 0.8 airchanges per hour (ACH), while the templates for contemporary buildings utilize an infiltration rate of 0.5 ACH based on updated buildings codes (Table 3). For the sake of this model, the year of last major renovation is considered to be the year of construction, with the assumption that a renovation significant

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\(^5\) Demographic information for this study was obtained from the American Community Survey (ACS) 2010–2014 (5-Year Estimates).

\(^6\) For this study, the assumptions were arbitrary and served simply to allow for an exploration of the effects of different user profiles. Future studies should review and refine these assumptions.
enough to require a permit will result in the major systems of the building (i.e. heating systems, building envelope, etc.) being upgraded. More information on the assumptions made in this step are listed in Appendix ____.

Table 3: Infiltration rates utilized in this model for each time period.

<table>
<thead>
<tr>
<th>Year of Construction</th>
<th>Infiltration Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-1950</td>
<td>0.9</td>
</tr>
<tr>
<td>1951-1980</td>
<td>0.9</td>
</tr>
<tr>
<td>1981-2000</td>
<td>0.6</td>
</tr>
<tr>
<td>2001- Present</td>
<td>0.5</td>
</tr>
</tbody>
</table>

1b. Model Generation

Once the local weather data, building geometries, and building construction and usage data were established and formatted appropriately, they were combined in a thermal simulation model. For this study, the workflow established in the city-wide study of Boston was utilized (Cerezo Davila, Reinhart, & Bemis, 2016). Using the parametric Rhino plugin Grasshopper, the non-geometric thermal properties associated with each building template were applied to each building in the study area according to its archetype classification. Multi-zone thermal models were created for each building, and shading calculations and the thermal interactions between buildings were accounting for using custom C# applications. Finally, the dynamic energy simulation engine EnergyPlus was used to generate an executable building-specific energy model for each parcel in the study area.

1c: Model Simulation

At this point, four energy models had been built for each building—one for each user type. Each simulation was executed independently using the EnergyPlus simulation engine, producing results in the form of annual energy consumption by load type by parcel. Since each energy model is executed independently, a CSV file with results is generated for each parcel. UBEM is computational intensive process, so the simulations were distributed between two 16 core computers to minimize simulation time.

It is important to note that a key step in UBEM is calibrating the model to real-world energy consumption data. However, datasets for measured electricity or fuel consumption were available to calibrate the model. In the absence of these datasets, the results were compared against typical residential energy consumption values reported in the Residential Building Energy Consumption Survey (RBECS) published by the USE Energy Information Administration (USEIA 2009). Nevertheless, the accuracy of the model could be greatly improved by calibrating it to site-specific energy consumption data from the Dudley Triangle neighborhood.

1d. Demographic Correlation

As mentioned previously, four simulations were run for each parcel—one for each user type. The final step in creating the baseline model was to assign each building the appropriate user type based on demographic data. However, demographic data is only reported at the level of the census block group—a geographic area roughly the size of a city block. Therefore, the appropriate user type was established at the block group level, and then applied all buildings within that block group—a necessary approximation given the limitations of data available. To do so, census data from the American Community Survey (ACS) 2010-2014 (5-Year Estimates) was obtained for the seven block groups in the Dudley Triangle neighborhood. Based on this data, rough approximations of the fraction of each user type were calculated.
Finally, these proportions were applied to the energy consumption data to correlate the energy simulations results to the actual demographics in the neighborhood (Table 4).

### Table 4: Dudley Triangle Demographics by Block Group

<table>
<thead>
<tr>
<th>Census Tract</th>
<th>Block Group</th>
<th>Families</th>
<th>Elderly Couples</th>
<th>Students</th>
<th>Young Professionals</th>
<th>Income Ranking (1= highest)</th>
<th>Percent of Units Occupied by Renters</th>
</tr>
</thead>
<tbody>
<tr>
<td>90400</td>
<td>3</td>
<td>0.53</td>
<td>0.18</td>
<td>0.11</td>
<td>0.18</td>
<td>1</td>
<td>0.61</td>
</tr>
<tr>
<td>90400</td>
<td>4</td>
<td>0.43</td>
<td>0.09</td>
<td>0.21</td>
<td>0.27</td>
<td>3</td>
<td>0.68</td>
</tr>
<tr>
<td>80100</td>
<td>1</td>
<td>0.23</td>
<td>0.20</td>
<td>0.54</td>
<td>0.02</td>
<td>7</td>
<td>0.67</td>
</tr>
<tr>
<td>80100</td>
<td>2</td>
<td>0.47</td>
<td>0.02</td>
<td>0.05</td>
<td>0.46</td>
<td>5</td>
<td>0.71</td>
</tr>
<tr>
<td>90600</td>
<td>1</td>
<td>0.40</td>
<td>0.08</td>
<td>0.13</td>
<td>0.39</td>
<td>2</td>
<td>0.60</td>
</tr>
<tr>
<td>90600</td>
<td>2</td>
<td>0.44</td>
<td>0.19</td>
<td>0.07</td>
<td>0.30</td>
<td>4</td>
<td>0.58</td>
</tr>
<tr>
<td>91300</td>
<td>2</td>
<td>0.47</td>
<td>0.16</td>
<td>0.12</td>
<td>0.25</td>
<td>6</td>
<td>0.87</td>
</tr>
</tbody>
</table>

### Part 2: Modeling the Impacts of ECMs

Next, a comprehensive list of all potential energy conservation measures (ECMs) for residential buildings was developed based on an understanding of residential construction methods, materials, and heating, cooling, and ventilation systems. The list was then narrowed to a set of nine basic ECMs that would be analyzed in this study. Due to time limitations, water conservation measures (including low flow showers and faucets) and behavioral changes (such as modifying thermostat set-points and schedules) were not included in the scope of this project. The nine measures were then broken into two categories based on ease of implementation. Projects that could be implemented in approximately one day with minimal expertise and few logistical barriers were considered “short term” projects; while those that required more extensive funds, knowledge, and planning were considered “long term” (Table 5). In this study, short term projects were called “ECM 1” and long-term projects were called “ECM 2” for simplicity. By breaking the measures up by ease of implementation—which is closely linked to the barriers residents experience—policy recommendations could be developed accordingly.

### Table 5: ECMs with Corresponding Timelines and Impacts

<table>
<thead>
<tr>
<th>Category</th>
<th>Implementation Time</th>
<th>Description</th>
<th>Key Impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short term</td>
<td>One Day</td>
<td>Upgrade light bulbs to LED</td>
<td>Decreased lighting density</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Weatherizing doors and windows</td>
<td>Decreased infiltration rates</td>
</tr>
<tr>
<td>Long Term</td>
<td>Requires Substantial Planning</td>
<td>Upgrade appliances: dishwasher, clothes washer, refrigerator, etc.</td>
<td>Decreased equipment density</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Upgrade heating system</td>
<td>Increased total heating COP</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Increase attic insulation</td>
<td>Decreased attic U-value</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Increase basement insulation</td>
<td>Decreased wall and ceiling U-value</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Window upgrades</td>
<td>Decreased window U-value</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Upgrade cooling system</td>
<td>Increased total cooling COP</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Increase wall insulation</td>
<td>Decreased wall U-value</td>
</tr>
</tbody>
</table>

The ECMs were then organized into two types of efforts: those that were independent of occupant density and human behavior (e.g. those related to the building envelope or mechanical systems), and those that

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7 Ease of implementation refers to a cumulative measure of the time, labor, and logistics involved in implementing an energy conservation measure.
are dependent on occupant density and human behavior (Table 6). For the former category, referred to as “building system upgrades”, contemporary building codes were used to quantify the impact of each ECM\(^8\). For the latter category, referred to as “occupant-based” ECMs, revised calculations based on lighting and equipment upgrades produced new values for lighting and plug loads. More information on the assumptions made in this step are listed in the Appendix. Once the impact of each ECM measure was established, revised templates were created for the ECM 1 and ECM 2 categories. At this point, Steps 1b-1d were repeated using the new templates. When this was complete, three energy consumption records existed for each building—“baseline”, ECM 1, and ECM 2—allowing for a comparison of the potential reductions in energy consumption associated with each retrofit level.

Table 6: Building System Upgrades vs. Human Behavior-Based ECMs.

<table>
<thead>
<tr>
<th>Building System Upgrades</th>
<th>Occupant-Based ECMs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weatherization</td>
<td>Plug load usage patterns</td>
</tr>
<tr>
<td>Increasing insulation</td>
<td>Lighting upgrades</td>
</tr>
<tr>
<td>Heating System Upgrades</td>
<td></td>
</tr>
<tr>
<td>Cooling System Upgrades</td>
<td></td>
</tr>
<tr>
<td>Window Upgrades</td>
<td></td>
</tr>
</tbody>
</table>

Figure 8: ECMs Analyzed in Study and Implementation Categories (ECM 1 = short term, ECM 2 = long term)

\(^8\) ASHRAE 90.1 2013, ASHRAE 90.2-2001, and ASHRAE 119-1988 RA 2004
Part 3: Adopter Characteristics

Once the energy simulations were complete, demographics were explored in more depth to determine where ECM implementation was most likely to occur. According to the adopter characteristics outlined in the literature review, the earliest adopters tend to have higher incomes and more education as compared with later adopters (see page 12). In addition, younger individuals tend to be more open to new technology than older individuals. Finally, homeowners experience fewer barriers in adopting energy conservation measures than renters.

To better understand these factors in the context of Dudley Triangle, census data was again utilized. Information on total population, median age, median household income, educational attainment, and homeownership status was obtained for each of the seven block groups in Dudley Triangle. Next, each of the block groups were ranked from 1-7 for each category, with a 1 indicating the highest level of receptivity to energy conservation measures. Finally, a weighting mechanism was applied to each category to attribute more significance to categories thought to be more important in determining the likelihood of adoption. The weighted score allowed for an understanding of the block group with the fewest barriers to ECM implementation (represented by the lowest score) and the block group with the greatest barriers to ECM implementation (represented by the highest score).

Table 7: Scorecard assessing adopter receptiveness to energy conservation measure program.

<table>
<thead>
<tr>
<th>Category</th>
<th>Points</th>
<th>801001</th>
<th>801002</th>
<th>904003</th>
<th>904004</th>
<th>906001</th>
<th>906002</th>
<th>913002</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>5</td>
<td>7</td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>6</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>Education</td>
<td>20</td>
<td>7</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>6</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>Income</td>
<td>20</td>
<td>7</td>
<td>5</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>4</td>
<td>6</td>
</tr>
<tr>
<td>Home Owners</td>
<td>15</td>
<td>4</td>
<td>6</td>
<td>3</td>
<td>5</td>
<td>2</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>Weighted Score</td>
<td>375</td>
<td>235</td>
<td>95</td>
<td>215</td>
<td>220</td>
<td>220</td>
<td>320</td>
<td></td>
</tr>
</tbody>
</table>

Part 4: Finances

Finally, financial options were explored in order to understand the feasibility of implementation for the various ECM measures identified. A thorough review of federal, state, and local programs was conducted and the options for Dudley Triangle residents documented. This information provided a pivotal link in relating the results of the energy simulations to real-world planning scenarios. As the adoption literature suggests, financial constraints are a significant barrier to the majority of residents, and overcoming this challenge presents an important part of long-term sustainability planning.

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9 Census data obtained from American Community Survey 5 Year Estimates 2010-2014.
10 Since data on the significance of each category was not available, the weighting scheme utilized here was arbitrary and served only to explore the potential effects of adoption characteristics on the spatial and temporal pattern of adoption in a neighborhood. Future research should explore significance of each factor in determining adopter characteristics.
Results

Total potential for reduction

The total energy consumption for existing residential buildings in the study area is estimated to be roughly 36.5 million kilowatt hours per year. After implementing simple ECMs—including upgrading incandescent lightbulbs to LED lightbulbs and weatherizing homes—annual energy consumption for the neighborhood is reduced to 30.1 million kilowatt hours per year, representing a reduction of 17.4%. When all homes are completely retrofitted to have optimal insulation in the walls and roofs, and energy efficient appliances, lights, windows, heating, cooling, and ventilation equipment, neighborhood energy consumption is reduced to 14.5 million kWh, a reduction from baseline levels of roughly 60%.

The installation of photovoltaic systems can further offset neighborhood energy consumption. Mapdwell, an online platform for estimating potential solar production, was utilized to estimate total neighborhood potential for the production of electricity through rooftop photovoltaic arrays. The combined solar potential for the 435 buildings in the study area amounted to 3.99 million kWh/year. Once this amount is subtracted from the energy consumption of the fully retrofitted homes, the net energy consumption for the neighborhood is 71% lower than the baseline energy consumption.

Comparing “What-If” Scenarios

Next, a number of “what-if” scenarios that account for the variation in both building type and household type were compared in order to understand which efforts should be prioritized given the constraints of limited time and financial resources. Figure 10 depicts a variety of “what-if” scenarios that incorporate demographics alongside benchmarks that represent Boston’s greenhouse gas reduction goal. The scenarios chosen for comparison were based on the most common barriers, including homeownership, income, and building vintage. These scenarios explore the reductions possible if the barriers are not

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11 This chart depicts a simplified version of Boston’s greenhouse gas reduction goal. It illustrates 20% and 80% reductions in energy consumption from the simulated baseline. In contrast, Boston’s goal is city-wide (e.g. not every building or neighborhood needs to achieve the same reductions, as long as the city achieves the stated goals in aggregate), in terms of greenhouse gas emissions, not energy consumption (although they are closely linked), and utilizes a baseline of 2005, as opposed to the simulated data which is based on TMY data.
overcome, or if the resources are only available for more willing adopters. As Figure 10 demonstrates, when only homeowners completed full retrofits a 22% reduction in annual energy consumption is achieved. If the top two income brackets in the Dudley Triangle—for whom energy efficiency measures are more affordable—completed full retrofits to their homes, a net reduction of 39% is achieved. If households considered to be “poor or struggling”12 implemented only the low-cost measures (including weatherizing and changing lightbulbs), while the more economically stable residents completed full home retrofits, a reduction of 46% is achieved. Finally, if only the homes built before 1950 are fully retrofitted, a 52% reduction in annual energy consumption from the baseline is achieved.

![Figure 10: Total Neighborhood Energy Consumption after each energy conservation scenario is implemented](image)

**Adopter Characteristics**

Next, it’s important to consider that technology adoption is both a temporal and spatial phenomenon. Based on the information in Table 7 (page 21), it can be expected that Block Group 3 of Census Tract 0904 will have the largest proportion of Innovators and Early Adopters based on block group demographics. In contrast, Block Group 1 of Census Tract 0801 will experience greater barriers and therefore will likely have more Late Adopters and Laggards. This is represented spatially in Figure 11. The resulting pattern of technology adoption is explored in a hypothetical scenario in Figure 12, which demonstrates the clustering effect associated with adopter characteristics. This pattern is particularly pronounced here since demographics (and therefore the adopter characteristics) were analyzed at a block group level, meaning that all households in each block group were assigned the same demographics (since that was the finest level of demographic detail available). In reality, technology happens on a household by household level (and may even vary within a single household), so the neighborhood patterns of technology diffusion will be somewhat more mixed that in the simplistic depiction of Figure 12.

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12 Defined as the population with a score of 2.0 or under in Table 118 of the American Community Survey 5 Year Estimates 2010-2014.
Figure 11: Block groups with the highest (in red) and lowest (in green) barriers to ECM implementation

Figure 12: Expected technology diffusion pattern if barriers are not addressed (blue = retrofitted, red = not retrofitted). Represents first 100 buildings to implement ECM.

13 This map is intended to be exploratory only and aims simply to visualize how the different barriers that households experience effects their receptivity to ECMs — household decisions will obviously vary.
Finances

Once the simulations were complete, a financial analysis was conducted to better understand which measures could realistically be implemented. This analysis builds off the "what-if" scenario exploration to determine which of those strategies are viable. The database of State Incentives for Renewables and Efficiency lists 99 programs for the state of Massachusetts, the vast majority of which are financial incentives (Database of State Incentives for Renewables & Efficiency, n.d.). Many of these incentive programs are facilitated by Mass Save, an initiative sponsored by the natural gas and electric utilities in partnership with energy efficiency service providers (Mass Save, 2016). The Mass Save program offers rebates for home appliances including clothes dryers, dehumidifiers, central air conditioners, water heaters, wireless and programmable thermostats, and more. In addition, Mass Save offers 0% loans for energy efficiency improvements, discounted pricing on energy efficient lightbulbs, and insulation incentives worth up to $2000.

Beyond simple rebates and incentives for individual measures, a number of other programs take a more comprehensive approach. Mass Save facilitates the Low Income Multi-Family Energy Retrofit, which involves multiple building audits and incorporates a variety of measures chosen on a case by case basis for each building. Based on the median incomes for the seven block groups in the Dudley Triangle, many of its residents may be eligible for this program.

Property Assessed Clean Energy (PACE) bonds are another financing option for homeowners. These bonds are issued by financial institutions to homeowners, who can use the proceeds to finance energy retrofits. The owners repay their loans over 20 years via an annual assessment on their property tax bill (Climate and Energy Resources for State, Local, and Tribal Governments, 2016). Since the bond is tied to the property, not the tenant, the bond stays with the building even upon its sale. This transfer is an important benefit to homeowners who may be wary of a 20 year loan commitment (What is PACE?, n.d.).

In addition, competitive pricing for renewable energy projects—including residential photovoltaic installations—is available through the Massachusetts Clean Energy Center (Solar, n.d.). Low interest, fixed-term loans are available to homeowners and residents, while the Solarize Massachusetts and Mass Solar Connect programs help to facilitate competitive pricing on projects. These programs are particularly relevant for neighborhoods like the Dudley Triangle, which has a strong organizational capacity thanks to DSNI.

Finally, in 2010, Massachusetts authorized local governments to establish an Energy Revolving Loan Fund to provide financing to private property owners for energy efficiency and renewable energy improvements (Database of State Incentives for Renewables & Efficiency, n.d.). While the impetus is on local governments to establish the program, Massachusetts Relief Bill H.B. 4877 provides the legal backing.

Discussion

Total potential for reduction

A number of important conclusions can be drawn from the simulation results. First, the 71% reduction from baseline conditions achieved through comprehensive energy efficiency retrofits and PV installation is striking, and underscores the potential energy savings that still exist in residential buildings in the Dudley Triangle—and likely elsewhere across the city. Second, it is encouraging to see the impact that simple measures—including replacing incandescent bulbs with LEDs and weatherizing homes—can have on energy consumption. If all homes across the Dudley Triangle implemented these simple measures, an annual reduction in energy consumption of 17% can be achieved. While whole-home retrofits can be expensive, logistically challenging, and time intensive—and are additionally complex in renter households—weatherizations and light bulb replacements can be performed for a relatively low cost,
require minimal expertise, and can be completed by tenants. These savings represent low-hanging fruit that can be completed in the short-term to make a significant dent in annual energy consumption. Finally, the installation of photovoltaic arrays (PV) on all residences can further offset neighborhood energy consumption. While the gains achieved from this measure are significant, they are dwarfed by the gains from the whole-home retrofits. Therefore, it's clear that the whole-home retrofits are the most impactful measure, and should be prioritized when possible. Nevertheless, these measures are not mutually exclusive, and each household may present more favorable conditions for one or the other. Therefore, both whole home retrofits and PV installations should be pursued in tandem to obtain the most energy savings possible.

Comparing “What-If” Scenarios

Figure 10 depicts the total energy consumption after a variety of energy reduction strategies are implemented based on demographics. This representation presents a powerful way to think about and plan for energy reduction programs. Recognizing that some of the target groups will experience fewer barriers in implementing energy conservation measures (such as homeowners, as opposed to renters, who are generally not the decision makers for their buildings) allows for a differentiated approach that reflects the varying complexity of project implementation.

It is also useful to consider the capacity various income brackets may have. The costs of energy conservation measures can vary greatly due to existing conditions in each building. Added costs may be incurred if a building needs to be brought up to code, or if a health hazard is discovered during a home energy audit. For instance, mold issues, faulty wiring, and asbestos remediation can all drive up the costs of energy retrofit projects. Therefore, it is challenging to obtain accurate estimations regarding average cost for each energy conservation measure (see Recommendations). Nevertheless, assuming a fixed cost of $5000, there is still a significant spectrum of affordability within the relatively small geography of the Dudley Triangle area. According to census data provided in the American Community Survey (ACS) 2010–2014 (5-Year Estimates), lowest median income for a block group in the Dudley Triangle is $27,194, while the highest median income for a block group in the Dudley Triangle is $51,071. This means that a $5,000 energy conservation measure would represent 18% of the annual income for a household that is earning the median wage for the lowest earning block group—a potentially insurmountable expense. The same expense for a family earning the median annual income for the highest earning block group would represent 10% of their annual income—still a significant investment, but almost half that of the lowest earning block group. Furthermore, roughly 47% of the population residing in the Dudley Triangle neighborhood is considered to be “poor or struggling.”¹⁴ If an energy efficiency program is to be effective, it needs to account for the financial reality of its target group and ensure that implementing energy efficiency measures does not place an additional financial burden on families already struggling to make ends meet.

Finally, it is interesting to note that a vast majority of the potential savings can be achieved simply by retrofitting the oldest homes (defined as those built before 1950) to meet today’s standards of energy efficiency (Figure 10). Approximately 65% of the residences in the Dudley Triangle were built before 1950. It is clear that the most significant gains can be achieved by focusing efforts on these residences. This type of information provides valuable information to shape an effective neighborhood energy reduction program.

Adopter Characteristics

Not all households are equally equipped to implement energy conservation measures. As Figure 2 (page 12) indicates, adoption happens over time, and different households adopt at different times based on their adopter characteristics. Adopter characteristics are complex and nuanced, and the assessment of adopter

¹⁴ American Community Survey (ACS) 2010–2014 (5-Year Estimates) Table 118.
characteristics presented in this study are coarse and simplified. For instance, this study failed to account for the manner in which one's neighbor's decision to adopt a new technology changes the probability of adoption for an individual (Cantono & Silverberg, 2009). Nevertheless, this study effectively illustrates the importance of adopter characteristics in determining the spatial and temporal patterns of technology diffusion. In this case, median household age, median household income, educational attainment level, and homeownership status were used as a simplified set of factors that determined a neighborhood's adopter characteristics. Future studies should explore these factors in more depth, and should correlate the weighted scores to real-world outcomes in order to verify their accuracy.

Based on the results of the adopter characteristics scorecard, it is clear that some block groups in the Dudley Triangle face considerably higher barriers than others. It is critical that a targeted, neighborhood-based energy efficiency program address the barriers associated with each population segment and account for varying priorities in order to achieve widespread adoption of energy efficiency measures. For instance, when targeting Innovators, who are more likely to make decisions based on values, the environmental impact of an energy efficiency measure should be underscored. In contrast, the Late Adopters are more likely to make decisions based on financial necessity. Therefore, small financial incentives are likely to be more effective in impacting the behavior of this group, while they are less of a motivating factor for the Innovators.

**Finances**

While there are a plethora of financial programs available to Boston residents, the vast majority place the burden of responsibility on residents. From rebates and incentives, to low or no interest loans, to discounts on pricing, these programs rely on residents to take the initiative. While this approach may work for Innovators, technology diffusion research suggests they consist of less than 3% of the population. A more thoughtful approach is required to reach the mainstream and achieve widespread adoption. A more impactful financial program is explored below.

**An Action Plan for the Dudley Triangle**

Based on the simulation results, two specific approaches to energy reduction stand out—retrofitting all homes built before 1950, and weatherizing all homes and installing energy efficient lighting. When these two measures are combined, significant savings can be achieved. Figure 13 depicts the change in energy consumption over time if 10 of the oldest homes complete deep retrofits each year, until all homes built before 1950 have been retrofitted, and 50 homes per year complete “simple ECMs”. At this rate, by 2044 all of the homes built before 1950 will have been fully retrofitted, and all other homes will have been weatherized and equipped with energy efficient lightbulbs. The total energy reduction these measures will have achieved is 55%. If photovoltaic panels were installed on one third of the households in the study area, the net energy consumption could be further reduced by 1.3 million kWh/year, or 4% of the baseline energy consumption.
In order to achieve the above goals, a neighborhood-based approach should be utilized. DSNI has an important role to play as a community anchor and can leverage its position as a community partner in a number of important ways. First, it should provide subject matter expertise to residents. Instead of individual residents having to research the available programs, learn how to apply, and navigate a complicated implementation process, a centralized point person should be tasked with learning the process and providing expertise to the community—thus achieving economies of scale. Second, DSNI should finance and manage the installation of solar panels throughout the neighborhood. This would take the financial, logistical, and time burdens off residents, and the whole community would benefit by having a renewable source of energy and a source of income. Third, DSNI should manage an energy fund for residents that provides funding for renewable energy and energy efficiency projects. And finally, by assisting with project management and aggregating projects, DSNI can help to achieve better pricing on goods and services.

For example, Mapdwell estimations suggest that if solar photovoltaic arrays were installed on every residential rooftop in the Dudley Triangle, a total production of 3.98 million kWh/year can be realized, producing an average annual revenue of $1.38 million (Mapdwell, n.d.). Assuming one third of homes in the Dudley Triangle install solar panels on their roofs, the annual production would amount to 1.33 million kWh/year, with an average annual revenue of $460,000. If DSNI was to finance the installation of the solar panels instead of homeowners—allowing for a centralized process and eliminating the need for individual homeowners to accumulate additional debt—half the annual revenue could be used to pay back the loans, while the remaining revenue could finance energy efficiency projects and provide free (or discounted) electricity to Dudley Triangle residents. In other words, for every dollar in revenue obtained through the sale of electricity and Sustainable Renewable Energy Credits (SRECS), $0.50 would service the loan that financed the panels, $0.25 would go to the homeowner, and $0.25 would go to the neighborhood energy efficiency fund—which can ensure further utility bill reductions for homeowners through additional energy efficiency projects. While this scenario is just one option among many for financing, it demonstrates how the organizational capacity DSNI brings to the neighborhood is a valuable resource that can allow the neighborhood to achieve energy savings beyond those that traditional means have been able to achieve.
The City of Boston should also contribute to the neighborhood energy efficiency and renewable energy revolving fund for three important reasons. First, neighborhood-based energy efficiency programs are the most effective approaches to achieving the widespread adoption of residential energy efficiency measures. Supporting these types of programs is an important way Boston can capitalize on opportunities for energy efficiency and make progress towards meeting its greenhouse gas reduction goal. Second, neighborhood-based energy efficiency programs keep wealth in local communities by reducing the financial burdens that utility bills place on residents (which disproportionately affects low-income residents). Finally, neighborhood-based energy efficiency programs support local jobs. A broad range of occupations benefit from these types of programs including energy auditors, electricians, carpenters, insulation workers, construction managers, building inspectors, neighborhood energy managers, community organizers, and more.

**Conclusion**

This study has explored how urban energy modeling (UBEM) can be utilized to explore the impacts of various energy conservation measures. First, the total potential reduction of each set of measures was explored. Next, demographic data and building data was incorporated to create more informed strategies for energy reduction. UBEM provides a new tool that can inform policy and programmatic decision making.

Technology diffusion literature informed an analysis of the factors that affect the likelihood of adopting energy conservation measures. Parameters such as income, homeownership status, education level, and age were identified as relevant. A weighting mechanism was utilized to explore the effects these factors have on the temporal and spatial patterns of technology adoption. By combining census data with energy consumption simulations, the opportunities and barriers can be understood for each block group and can inform a neighborhood-based energy efficiency program accordingly.

Finally, based on the results from the energy simulations, the incorporation of census data, and the implications of the technology diffusion literature, an action plan was developed for the Dudley Triangle.
Furthermore, since it was clear that the existing financial programs were not addressing some of the main barriers to achieving widespread residential energy efficiency, an innovative proposal for an organizational and financial structure was developed. If implemented, this program would reduce utility burdens on Dudley Triangle residents, support local jobs, and improve the environmental sustainability of the neighborhood.

Limitations of this study

To the author's knowledge, this study is the first UBEM to incorporate demographic data and technology diffusion research. While it represents an important milestone in the urban energy modeling field, significant limitations were experienced. First, UBEMs need to be calibrated based on actual energy consumption data so that the assumptions can be adjusted to match real-world conditions. However, during the course of this study, actual energy consumption data for the residences in the Dudley Triangle was not able to be obtained, and so the data remains approximate at best. Furthermore, UBEMs are not intended (and should not be used) to assess the savings associated with individual buildings. The purpose is to identify savings in aggregate across an urban scale. In practice, an energy audit conducted by a professional is the recommended starting point to assess the potential energy savings associated with energy conservation measures in an individual building.

Second, different datasets utilized different levels of granularity. GIS shapefiles and tax assessor data provides information at the scale of individual buildings. In contrast, census data regarding household demographics is only available at the block group level. Therefore, some assumptions were required. For instance, the weighting scheme used to correlate the user profiles to the buildings in a block group was based on the aggregate demographics of the block group. The weighting scheme was then applied to all the buildings within the block group. This approach was useful in depicting the influence of demographics and user profiles on urban energy consumption, but again is not accurate at the scale of individual buildings and should not be considered as such.

Finally, the user profiles did not align perfectly with the demographic categories utilized by the census. Therefore, assumptions were required about which census categories correlated to each user profile (see Appendix ____). While the assumptions are considered to be reasonable, they clearly do not hold true for every household. The limited number of user profiles, the associated assumptions about behavior, and the manner in which households were assigned a user profile likely involves a margin of error. Establishing what this margin of error is should be the subject of future inquiry.

Challenges Identified

The most challenging aspect of this study was the lack of readily available data. Building energy consumption data for Dudley Triangle—or any similar geography—was not readily available, nor were the average costs associated with any of the energy conservation measures of interest, or their estimated impacts on energy consumption. Finally, the rates of diffusion for energy conservation measures are currently unknown. For now, educated assumptions had to suffice. Better information on these metrics would improve the accuracy of the energy model, allow for a more granular assessment of project affordability, and allow for a better understanding of how implementation strategies effect adoption rates. An up-to-date database of energy efficiency project costs, timelines, impacts, problems, barriers, etc. on a neighborhood level across the city would go a long way towards addressing this challenge.

Opportunities for further exploration

While this thesis has provided a useful and informative high level look at the impacts of energy efficiency measures in residential buildings in Boston, the time and capacity limitations of this project inevitably meant that many elements could not be explored. These tangential paths would provide an excellent
complement to data and analysis presented in this thesis, and present useful opportunities for future work. Together, they would provide a more comprehensive analysis of increasing robustness and depth:

**Calibration of the baseline energy model**

For the purposes of this study, the baseline energy model was not calibrated in a robust manner. Energy consumption data for the study area(s) was not readily available, making calibration a challenge. Furthermore, time limitations required that only a high level of calibration was completed. Therefore, the baseline model was compared only to RECS data (expand on what this is and what exact data was used). The robustness of the model would be greatly improved if actual energy consumption data for the two neighborhoods could be obtained, and the model correlated to the data.

**Exploration of confidence intervals in the energy savings estimations**

For the purposes of this study, the energy savings associated with each energy conservation measure was approximated. While single approximations simplified the modeling process, and the time and computing power needed, it fails to account for inevitable variations in the actual savings achieved. Statistical accuracy would require the use of confidence intervals that can account for probability effects of energy savings. The accuracy and robustness of this model could be increased if the impacts of energy conservation measures was modeled again, but using confidence intervals for the predicted savings of each measure.

**Comparison of estimated energy savings to actual energy savings associated with energy conservation measures**

Throughout the course of our research, we struggled to find any data on the actual energy savings associated with energy conservation measures. Industry estimates are invariably broad and therefore make putting actual numbers to estimates difficult. A robust assessment of actual energy savings data associated with real-world energy conservation measure projects would be extremely valuable for all future studies.

**A detailed quantification of costs associated with energy conservation measures.**

Similarly, hard numbers on the costs associated with each energy conservation measure studied was nearly impossible to come by. Affordability was a major priority in this study, and without understanding the associated costs, it made a robust analysis of affordability difficult. It would be extremely valuable to develop a comprehensive understanding of the costs of a statistically significant number of energy conservation measures for a given geography, as well as the most common issues that caused prices to inflate beyond expectations.

**Explore effects of aggregating energy conservation project, rather than doing them on an individual basis**

A literature review turned up virtually no sources that compare the effects of aggregating energy conservation projects. One would expect that higher levels of implementation and lower costs can be achieved when multiple small projects are combined. It would be useful to explore this theory in more depth and to determine if, and by how much, and effect it has on project costs and adoption rates.

**Other opportunities for further study**

The various opportunities for further study outlined above all relate to the improving the cost and energy savings estimations associated with implementing energy conservation measures in residential homes. In addition to these important opportunities for further study, the quantitative results can also be taken in a variety of different directions. For instance, it would be interesting to assess the job impacts of
implementing energy conservation measures in Boston. One could identify the required actions necessary to meet Boston’s greenhouse gas reduction goal (as described in this study or others), and then assess whether there is a trained and ready workforce for implementing these measures. If not, what type of training programs would be necessary? What kinds of jobs would benefit the most? Would more individuals need to be hired? In what fields? What type of training programs should be established? For this type of analysis, one could draw heavily on work done by the Green Justice Coalition. In addition, one could explore an implementation and outreach approach to aid the City of Boston in rolling out a residential energy efficiency program. For such a study, one could draw heavily on literature surrounding Community-Based programs, and on the successes and challenges of past programs in Boston and elsewhere.

Given the time and capacity of this project, the scope of the undertaking was invariably limited to a high level analysis of energy conservation impacts and the policy implications. Nevertheless, it provides an important first look at potential savings, affordability metrics, and options for implementation. The urban modeling approach allowed for an assessment of building to building interactions (including heat exchange, shading, and other effects), while also allowing for a geospatial analysis that incorporated demographics and neighborhood characteristics. It is the hope of the author that this paper can contribute to the literature on urban energy modeling and how it can be used to inform public policy. Ultimately, it aims to demonstrate how energy conservation strategies can be an important opportunity to create a more socially and economically equitable city, while furthering ecological goals.
Works Cited


Appendix A: UBEM Calculations and Assumptions

Energy Conservation Measures

1. **Weatherization:**
   - The main impact of weatherizing a home is to decrease infiltration rates. First, ANSI/ASHRAE 119-1988 RA 2004 was used to identify the appropriate infiltration rate for a new home in Massachusetts. Based on the climate region, this value was calculated as 0.66 ACH. This value was then improved by 30% to simulate a “high efficiency” scenario. The ASHRAE+30% value of 0.4 is used as the “upgraded” scenario—e.g. after a weatherization is complete.
   - To obtain values for existing homes, a number of assumptions are made, as follows:
     - Homes built after 2000 (1_4) are fairly efficient and therefore have infiltration rates of 0.5.
     - Homes built from 1980-2000 (1_3) are up to code, and therefore have infiltration rates of 0.6.
     - Homes built before 1980 (1_1 and 1_2) are drafty and therefore have infiltration rates of 0.9.

2. **Attic Insulation:**
   - The main impact of adding attic insulation to a home is to decrease the U-value of the roof. To calculate the appropriate R-values for existing buildings and upgraded insulation, ANSI/ASHRAE 90.1 2013 Table 5.5-5 is used. A number of assumptions were made, as follows:
     - The main variables that determine the U-value of the roof are roof type and age.
     - Homes built after 2000 (1_4) are highly efficient and therefore have a U-value of 0.15.
     - Homes built from 1980-2000 (1_3) have a U-value of 0.3.
     - Homes built between 1950 and 1980 (1_1) have a moderate amount of insulation, and therefore have a U-value of 0.5.
     - Homes built before 1950 have little to no insulation and therefore have a U-value of 0.8.
     - Retrofitted homes with additional insulation are assumed to have an attic U-value of 0.11.

3. **Basement Insulation:**
   - The main impact of adding basement insulation to a home is to increase the U-value of the foundation walls and the basement ceiling. To calculate the appropriate U-values for existing buildings and upgraded insulation, ANSI/ASHRAE 90.1 2013 Table 5.5-5 is used. A number of assumptions were made, as follows:
     - Homes built after 2000 comply with ASHRAE 90.1 2013 (basement wall U-value = 0.5; ground floor U-value = 0.18)
     - Homes built between 1950 and 1980 comply with (insert old text name here). The U-value of the basement walls for this period is assumed to be 1.0, and the U-value of the ground floor is assumed to be 0.45.
     - The values for time periods 1 (Pre-1950) and 3 (1980-2000) are roughly approximated based on values for periods 2 and 4 as follows: Pre-1950 basement wall U-value = 1.2, ground floor U-value = 3.0. 1980-2000 basement wall U-value = 0.8, ground floor U-value = 0.33.
Retrofitted homes with additional insulation are assumed to have a basement wall U-value of 0.5 and a ground floor U-value of 0.15.

4. Wall insulation:
   - The main impact of adding wall insulation to a home is to decrease the U-value of the wall. To calculate the appropriate U-values for existing buildings and upgraded insulation, ANSI/ASHRAE 90.1 2013 Table 5.5-5 is used. A number of assumptions were made, as follows:
     - The main variable that determines the U-value of the wall is age.
     - Homes built after 2000 (Period 4) are highly efficient and have a U-value of 0.31.
     - Homes built from 1980-2000 (Period 3) are up to code and have a U-value of 0.37.
     - Homes built before 1950 (Period 1) and between 1950 and 1980 (Period 2) have minimal insulation, resulting in U-values of 1.1 and 0.65, respectively.
     - Retrofitted homes with additional insulation are assumed to have a wall U-value of 0.25.

5. Heating System Upgrades:
   - The main impact of upgrading a heating system is to improve its coefficient of performance (COP). According to federal guidelines\(^{15}\), new heating systems should have a minimum efficiency standard of 75-80% AFUE. An “energy efficient” option may have an AFUE of 0.9-0.95. Based on these figures, the following assumptions have been made:
     - Heating systems in homes built before 1980 have most likely had the heating system upgraded—therefore the efficiency for these heating systems is assumed to be 0.8.
     - Heating systems in homes built from 1980-2000 are likely less efficient than those of today’s standards, so an efficiency of 0.77 is assumed.
     - Homes built from 2000-Present are assumed to have an efficiency of 0.85.
     - Energy efficient retrofits are expected to achieve efficiencies of 0.92.

6. Cooling System Upgrades
   - ASHRAE 2008 handbook was used to determine the appropriate COPs for cooling systems for each of the four time periods. Using this text as a guideline, the following assumptions were made:
     - Cooling systems in homes built before 1980 have most likely been upgraded—therefore the efficiency for these cooling systems is assumed to be 2.8.
     - Cooling systems in homes built from 1980-2000 are likely less efficient than those of today’s standards, so an efficiency of 2.5 is assumed.
     - Homes built from 2000-Present are assumed to have a cooling efficiency of 2.8.
     - Energy efficient retrofits are expected to achieve efficiencies of 3.2.

7. Window Upgrades
   - The main impact of upgrading windows is to decrease the U-value of the window. To calculate the appropriate U-values for existing buildings and upgraded windows, ANSI/ASHRAE 90.1 2013 Table 5.5-5 is used. A number of assumptions were made, as follows:

- Homes built before 1950 are assumed to have windows with a U-value of 3.122.
- Homes built between 1950 and 1980 are assumed to have windows with a U-value of 2.72.
- Homes built between 1980 and 2000 are assumed to have a U-value of 2.556.
- Homes built from 2000-Present are assumed to have a U-value of 2.2.
- Retrofitted, energy-efficient windows are assumed to have a U-value of 1.71.

**Building Structures and Neighborhood Data**

FY14 City of Boston Tax Assessment Data was utilized to determine property information about residences in the Dudley Triangle. Most of this information was readily available and was drawn directly from the tax assessor database without manipulation. However, the ratio of units to floors (UPF) was challenging to ascertain as there were inconsistencies in the data. The following processes were utilized in order to classify residences by UPF:

1. The structure type codes were replaced with descriptions based on the key in the FY14 Assessing Data CD Packet.
2. Columns R_BLDG_STY and S_BLDG_STY were combined into a single column called BLDG_STY
3. If the number of kitchens = the number of units, the data was considered consistent, and the building was classified immediately.
4. When the kitchen data was not available or did not match the number of units listed for the building, more investigation was needed, as follows:
   a. The total number of units appears to be accurate for condos—so all records with usetype CM were classified according to the # of units listed in TOTUN.
   b. All buildings where LU = R2 and BLDG_STY = Duplex are assumed to have two units and two kitchens.
   c. Notes:
      i. NUMFLOORS generally appears to be accurate--- so this is assumed to be the case for all records.
      ii. TOTUN is only accurate for records with CM as the usetype.
      iii. R_KITCH is only accurate for records that do not have CM as the usetype, and only holds true for records where NUM_FLOOR ≠0 and R_KITCH ≠ 0.
      iv. All E and EA units were investigated manually using GIS and Google Maps
      v. All other records where inconsistencies were found (e.g. if the number of floors ≠ 0 but the number of kitchens and the number of units ≠ 0) were investigated manually using GIS and Google Maps.

**User Profile Assumptions**

- User profiles are assumed to be independent of the type of structure. For each type of residence, all four user profiles are considered. It is also assumed that for a given multi-family building, all units have the same user profiles.

**Space Use Assumptions**

<table>
<thead>
<tr>
<th>Structure Type</th>
<th># Units/Floor</th>
<th>Total # of Units</th>
<th>Space breakdown per unit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Bedrooms</td>
</tr>
<tr>
<td>1</td>
<td>0.25</td>
<td>1</td>
<td>5</td>
</tr>
</tbody>
</table>
### Assumptions on Number of Light Bulbs per Space Type:

For family residents:
- 8 bulbs for two bedrooms (4 CFLs, 2 Incandescents, 2 LED)
- 6 bulbs per living room (3 CFLs, 3 Incandescents)
- 11 per kitchen (8 CFLs, 3 Incandescents)
- 5 per bathroom (5 CFLs)
- 3 per corridor (3 CFLs)

For young professionals:
- 10 bulbs for two bedrooms (6 CFLs, 4 LEDs)
- 8 bulbs per living room (6 CFLs, 2 LEDs)
- 10 per kitchen (6 CFLs, 4 LEDs)
- 6 per bathroom (6 CFLs)
- 6 per corridor (6 CFLs)

For elderly residents:
- 6 bulbs for two bedrooms (3 CFLs, 3 Incandescents)
- 5 bulbs per living room (2 CFLs, 3 Incandescents)
- 7 per kitchen (4 CFLs, 3 Incandescents)
- 4 per bathroom (4 CFLs)
- 2 per corridor (2 CFLs)

For young professionals:
- 10 bulbs for two bedrooms (6 CFLs, 4 LEDs)
- 8 bulbs per living room (6 CFLs, 2 LEDs)
- 10 per kitchen (6 CFLs, 4 LEDs)
- 6 per bathroom (6 CFLs)
- 6 per corridor (6 CFLs)

### Equipment Assumptions

- **Family Residents**
  - Living Room (1 TV, 0 laptop)
  - 2 Bedrooms (1 TV, 2 laptops)
  - 1 Kitchen (1 fridge, 1 electric stove, 1 washer, 1 dryer, 1 dishwasher, 1 other)

- **Young Professionals**
  - Living Room (1 TV, 0 laptop)
- Elderly Residents
  - 2 Bedrooms (1 TV, 4 laptops)
  - 1 Kitchen (1 fridge, 1 electric stove, 1 washer, 1 dryer, 1 dishwasher, 1 other)

- Students
  - 2 Bedrooms (0 TV, 4 laptops)
  - 1 Kitchen (1 fridge, 1 electric stove, 1 washer, 1 dryer, 1 dishwasher, 1 other)

**Occupancy Assumptions**

- Based on best guess estimates for number of occupants per unit for each occupancy type (4 for family residents, 3 for young professionals, 2 for elderly couples, 4 for students)
- Multiply the number of occupants by the number of units in each structure type and divide by the average area of that structure type to determine the occupant density (pp/m²)
Appendix B: Demographic Analysis Assumptions

Process for identifying weighted user types:

1. Calculations:
   a. The Total Population Under 18 was calculated as the sum of Tables SE_T007_002, SE_T007_003, SE_T007_004, and SE_T007_005
   b. The total population of adults over retirement age was calculated as the sum of Tables SE_T007_011, SE_T007_012, SE_T007_013
   c. Percent distributions is calculated as the number of households of each user type divided by the total number of households

2. Assumptions:
   a. All individuals 18-24 are students
   b. All elderly individuals live in pairs

3. User Assignments by Household:
   a. **User Type F**: Households: Households with one or More people under 18 Years (SE_T018_002)
   b. **User Type E**: Adults over retirement age divided by two (((SE_T007_011 + SE_T007_012 + SE_T007_013)/2)
   c. **User Type S**: Total Population: 18 to 24 Years (SE_T007_006) divided by Average Household Size (SE_T021_001)
   d. **User Type Y**: (Households: Nonfamily Households (SE_T017_007)) – (Student Households) – (Family Households) – (Elderly Households)

Table 1: American Community Survey Tables Used in Demographic Analysis

<table>
<thead>
<tr>
<th>Total Population: Under 5 Years</th>
<th>SE_T007_002</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Population: 5 to 9 Years</td>
<td>SE_T007_003</td>
</tr>
<tr>
<td>Total Population: 10 to 14 Years</td>
<td>SE_T007_004</td>
</tr>
<tr>
<td>Total Population: 15 to 17 Years</td>
<td>SE_T007_005</td>
</tr>
<tr>
<td>Total Population: 18 to 24 Years</td>
<td>SE_T007_006</td>
</tr>
<tr>
<td>Total Population: 25 to 34 Years</td>
<td>SE_T007_007</td>
</tr>
<tr>
<td>Total Population: 35 to 44 Years</td>
<td>SE_T007_008</td>
</tr>
<tr>
<td>Total Population: 45 to 54 Years</td>
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<tr>
<td>Total Population: 55 to 64 Years</td>
<td>SE_T007_010</td>
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<td>Total Population: 65 to 74 Years</td>
<td>SE_T007_011</td>
</tr>
<tr>
<td>Total Population: 75 to 84 Years</td>
<td>SE_T007_012</td>
</tr>
<tr>
<td>Total Population: 85 Years and over</td>
<td>SE_T007_013</td>
</tr>
<tr>
<td>Total Population</td>
<td>SE_T001_001</td>
</tr>
<tr>
<td>Total Population: 18 to 24 Years</td>
<td>SE_T007_006</td>
</tr>
<tr>
<td>Households:</td>
<td>SE_T017_001</td>
</tr>
<tr>
<td>Households: Family Households</td>
<td>SE_T017_002</td>
</tr>
<tr>
<td>Average Household Size</td>
<td>SE_T021_001</td>
</tr>
<tr>
<td>Households: Nonfamily Households</td>
<td>SE_T017_007</td>
</tr>
<tr>
<td>Households: Households with one or More people under 18 Years</td>
<td>SE_T018_002</td>
</tr>
</tbody>
</table>