

**Leveraging Human-environment Systems in
Residential Buildings for Aggregate Energy Efficiency
and Sustainability**

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ABSTRACT

Leveraging Human-environment Systems in Residential Buildings for Aggregate Energy

Efficiency and Sustainability

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Reducing the energy consumed in the built environment is a key objective in many sustainability initiatives. Existing energy saving methods have consisted of physical interventions to buildings and/or behavioral modifications of occupants. However, such methods may not only suffer from their own disadvantages, e.g. high cost and transient effect, but also lose aggregate energy saving potential due to the oftentimes-associated single-building-focused view and an isolated examination of occupant behaviors. This dissertation attempts to overcome the limitations of traditional energy saving research and practical approaches, and enhance residential building energy efficiency and sustainability by proposing innovative energy strategies from a holistic perspective of the aggregate human-environment systems. This holistic perspective features: (1) viewing buildings as mutual influences in the built environment, (2) leveraging both the individual and contextualized social aspects of occupant behaviors, and (3) incorporating interactions between the built environment and human behaviors. First, I integrate three interlinked components: buildings, residents, and the surrounding neighborhood, and quantify the potential energy savings to be gained from renovating buildings at the inter-building level and leveraging neighborhood-contextualized occupant social networks. Following the

confirmation of both the inter-building effect among buildings and occupants' interpersonal influence on energy conservation, I extend the research further by examining the synergy that may exist at the intersection between these "engineered" building networks and "social" peer networks, focusing specifically on the additional energy saving potential that could result from interactions between the two components. Finally, I seek to reach an alignment of the human and building environment subsystems by matching the thermostat preferences of each household with the thermal conditions within their apartment, and develop the Energy Saving Alignment Strategy to be considered in public housing assignment policy. This strategy and the inter-building level energy management strategies developed in my preceding research possess large-scale cost-effectiveness and may engender long-lasting influence compared with existing energy saving approaches. Building from the holistic framework of coupled human-environment systems, the findings of this research will advance knowledge of energy efficiency in the built environment and lead to the development of novel strategies to conserve energy in residential buildings.

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*Dedicated to my parents,
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Chapter 1

1. INTRODUCTION

1.1 The Energy Status Quo and Human-environment Systems

Energy consumption in the built environment constitutes a substantial portion of total energy use worldwide [1]. In 2010, the building sector accounted for more than 40% of U.S. primary energy consumption, split approximately equally between residential and commercial buildings, and was the largest of the three major energy consumption sectors (Fig. 1). The building sector alone contributed 7.4% to global carbon dioxide emissions [2]. As a result, reducing the energy consumed in the built environment is regarded as a key objective in many sustainability initiatives.

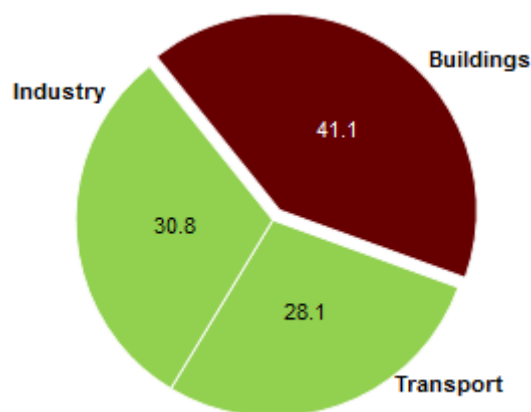


Figure 1. 2010 U.S. energy consumption by sector

The largest group of energy saving methods adopted to achieve energy reduction in the built environment has consisted of physical modifications to existing buildings and the choice of whether or not to make use of renewable energy [3]. The emphasis of most of the research

and energy efficiency strategies in this group has been to focus on the energy use of individual buildings. However, interventions designed to decrease the energy consumption of one building can have a significant impact on the thermal conditions of neighboring buildings, which varies depending on the spatial relationships of the buildings and the surrounding built environment [4]. Consequently, a narrow focus on these approaches can miss other opportunities for achieving optimized aggregate energy performance by, for example, improving the alignment of architectural and technical designs.

In addition to the energy savings lost due to a single-building-focused perspective, an energy-efficiency gap has been identified between intended and actual energy use by occupants [5]. A rebound effect has been observed as occupants' increased use of energy services is induced by the reduction in energy costs afforded by more efficient appliances and/or technologies [6]. Indeed, as buildings become more energy efficient, the behavior of their occupants plays an increasingly important role in energy consumption [7] with behavioral factors explaining, for example, about 30% of the variance in overall heating consumption and 50% in cooling consumption for typical buildings [8]. In the light of this phenomenon, another class of energy saving methods has begun to emerge as significant, which involves control and optimization techniques that are specifically targeted at occupant behaviors and encourage occupants to adopt energy conservation measures [3, 9].

Certain limitations affecting energy savings strategies based on engineering interventions and/or behavioral modification may actually impede the effectiveness and implementation of these strategies when efficiency and sustainability are valued. For example, interventions designed to improve the energy performance of the building itself and the advanced systems

required to monitor occupant behaviors can be costly and time-consuming to implement and maintain. In addition, while some behavioral strategies can achieve energy savings without the expense of added infrastructure, their effect is generally transient unless homeowners are motivated to periodically revisit their energy consumption patterns [6]. In the light of these shortcomings, a coordinated approach to human environment research, which lies at the core of sustainability science, deserves further exploration [10].

For the first time in history, the immediate human environment primarily consists of the built environment [11]. Human and environmental subsystems are intimately linked in such a way that any emphasis on a single “interacting” system stands in serious danger of reducing our understanding of social dynamics to a consideration of environmental dynamics, or vice versa [12]. Instead, interactions between these subsystems need to be considered, which requires a broader, more pluralistic and integrated approach to coupled human–environment systems than that applied in many past studies [10]. Thus, knowledge integration, the blending of concepts from two or more disciplines to explore innovative solutions, can make a major contribution to efforts to improve the sustainability of human activities in the built environment [13]. Based on this line of reasoning, this dissertation adopts an interdisciplinary approach to evaluate the integration and interaction of the built environment and the related human behaviors in order to identify novel strategies capable of supporting aggregate energy efficiency and sustainability more effectively.

1.2 Theoretical Background

1.2.1 Building Energy Simulation

Many different approaches to the prediction and improvement of energy use in buildings have

been proposed and applied in the process of building design, operation or retrofitting existing buildings [14]. Engineering methods for building energy analysis and simulation provide powerful tools based on the use of detailed building models that calculate thermal dynamics and energy behavior using physical principles [15]. For instance, EnergyPlus is a state-of-the-art whole-building energy simulation program developed by the U.S. Department of Energy that is capable of fully integrating external weather conditions, types of building construction, HVAC systems, operation schedules, water usage, and renewable energy [16]. Besides engineering methods, artificial intelligence (AI) has been developed and applied in several building energy applications, including forecasting, systems modeling, and equipment controls [17]. AI-based methods such as artificial neural networks (ANN), fuzzy logic, and genetic algorithms offer substantial advantages in modeling non-linear energy systems and have the capacity to incorporate various socio-economic conditions [18]. As the most widely used AI models in building energy [14], ANNs have been applied by researchers to predict energy consumption [19, 20] and energy savings from both building and equipment retrofits [21, 22], as well as other performance parameters [23].

Utilizing these available simulation tools, the energy consumption attributed to individual buildings has been extensively explored. With the goal of understanding how to optimize the energy efficiency of an individual building, energy consumption is generally evaluated by describing indoor thermal behavior, energy consumption, and building envelope features [15, 24]. More recent studies have begun to investigate the relationship between a building and its occupants by characterizing the building's energy performance relative to the occupants' behavior [25] and the typical occupancy schedules in each thermal zone [26].

To fully explore the potential for improving energy efficiency in the building sector beyond the interior thermal dynamics of a single building, some scholars propose a whole-building energy design concept [27], which is supported by research on energy modeling and simulation [28]. These advanced assessment procedures allow researchers to study the thermal behavior of realistic buildings under a variety of boundary conditions [29]. Using these procedures, several researchers have found evidence to indicate that environmental stresses typical of the local environment surrounding a building may have a large impact on that building's energy performance [30].

1.2.2 The Inter-building Effect

Energy consumption among groups of buildings differs from a simple sum of the energy consumed by the individual buildings because each building can have a significant impact on adjacent buildings' energy use. To realize the full potential energy reduction may, instead, require examining the energy consumption and conservation for a group of buildings. To date, the main research thrust for groups of buildings has generally focused on how mutual shading impacts adjacent buildings [31, 32]. The important effects of shading design were recognized by Olgyay as far back as 1957 [33]. Thereafter, in a study on solar radiation, the mutual shading of co-located buildings was found to significantly vary the thermal conditions of the two buildings [34]. Figure 2, modified from a published work [35], illustrates how this mutual impact varies with time. A CAD-embedded method has now been developed that assesses the effect of external elements such as other buildings and trees on building energy performance, with a particular focus on the collection of solar energy [36, 37].

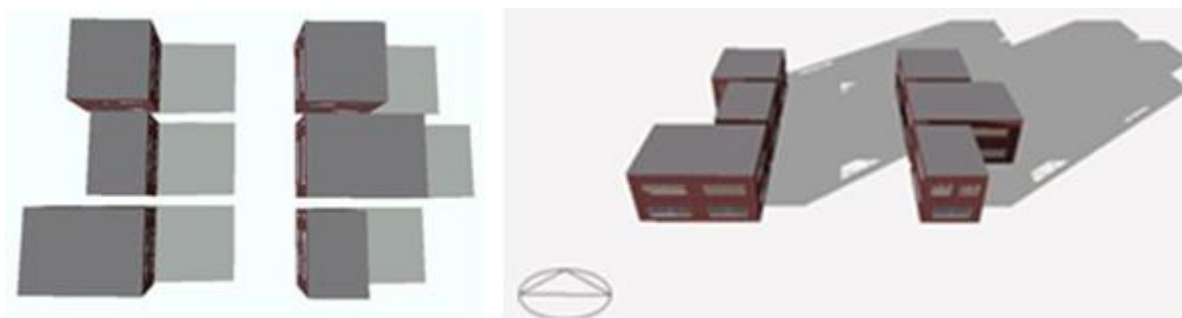


Figure 2. Mutual shading at 4 pm on the summer (left) and winter (right) solstices

Beyond shading phenomena, a more recent study has systematically evaluated how a combined Inter-building Effect on energy consumption could work and how it affects buildings' energy performance [4]. The *Inter-building Effect* (IBE) is defined as the impact on building energy consumption due to the close proximity of other buildings in an urban environment. The study revealed energy requirement modeling inaccuracies of up to 42% when the IBE is ignored in traditional approaches and demonstrated that the IBE created by the spatial relationship with surrounding buildings must be considered in order to accurately predict the energy performance of a building [4]. The research conducted for this dissertation therefore sought to enlarge the assessment perspective from a single building to an inter-building or inter-dwelling level in order to provide a more realistic assessment of network-wide energy efficiency.

1.2.3 The Influence of Occupant Behaviors on Energy Use

The adoption of intervention strategies aimed at residents' individual behaviors can lead to significant reductions in energy consumption [38]. An individual's energy consumption depends on a number of personal and social factors, including lifestyle choices and socioeconomic incentives among others. Wide variations in occupant habits, lifestyles, and perceptions of comfort result in a range of behaviors and preferences among households

regarding thermostat management and comfort requirements, for example [7]. Individual factors such as a preference for air conditioning while sleeping or working have been shown to have an impact on the energy required for space conditioning that is eight times higher than that of environmental factors [39]. To take advantage of such effects to reduce energy consumption, a notable current trend is to organize building operations around the optimum combination of energy savings and personal behavioral tendencies such as thermal comfort preference [40].

Rather than focus on the individual behavior of occupants, some researchers have emphasized the social aspects of behavior, particularly the interpersonal structure of relationships. The interpersonal connections among building residents can provide them with incentives that encourage them to consume less energy through information sharing and/or a motivation to keep up with peers who have adopted energy conservation practices. The influence of occupants' interpersonal relationships within those in their peer networks has been observed and empirically supported in experimental studies on energy consumption [41, 42]. The researchers found that a group of residents provided with information on their own and their peers' usage consumed 34% less energy than a control group within three days of receiving the information. The energy saving norm embedded in the social network was also observed to play a significant role in the energy savings encouraged by this feedback system. Leveraging this *Peer Network Effect* (PNE), where members of a peer group imitate or influence the behavior of others in the group, may significantly increase aggregate energy conservation in their communities and is thus an important focus of research [42].

Human behavior is highly situational, and the extent to which behavior is mutable for

energy conservation depends on the strength and proximity of contextual forces [43]. Surrounding buildings and residents, the neighborhood context plays a critical role in the formation, resulting structure and strength of occupants' social networks, especially when examined at the inter-building level as opposed to within a single building [44]. This is because the neighborhood provides locations where interpersonal relationships with others can be developed, which is important because people are attached to place-based social relationships [45]. Two factors have been reported to result in the dissemination of pro-environmental behaviors at the neighborhood level: residents' concern for the environment and pressure from neighbors and friends who were early participants [46]. Thus, the neighborhood context should be taken into account in an inclusive model in order to capitalize on the social aspects of occupant behaviors for energy conservation.

1.3 Research Questions and Format of Dissertation

This research conducted for this dissertation attempts to overcome the limitations of traditional energy saving research and practical approaches, and enhance residential building energy efficiency and sustainability by proposing innovative energy strategies based on the current trend of capitalizing on human-environment systems. The research adopts a holistic perspective of the aggregate human-environment systems by (1) viewing buildings as mutual influences in the built environment, (2) leveraging both the individual and contextualized social aspects of occupant behaviors, and (3) incorporating interactions between the built environment and human behaviors. To implement this interdisciplinary research framework, the work utilizes both engineering tools, such as building energy simulations, and social science approaches, such as social network analysis and policy studies. The dissertation

follows a three-paper format. The research questions investigated in each paper are as follows:

1. How could leveraging neighborhood contextualized occupant social networks affect energy conservation performance at the inter-building level above and beyond efficiencies gained through typical physical building retrofits?
2. Does a synergy exist at the intersection of building networks and residents' social networks such that additional energy savings can be achieved beyond leveraging either network in isolation?
3. Could alignment of occupant thermostat preferences with the building thermal environment lead to significant energy saving?

The first paper (Chapter 2) adopts an aggregate view at the inter-building level that systematically examines three interlinked factors: buildings, residents and their surrounding neighborhood. Based on the known facts that buildings' mutual impacts and contextualized occupant behaviors influence energy consumption, this paper aims to fill a research gap by quantifying the potential energy savings to be gained from renovating buildings and leveraging occupant social networks derived from neighborhood affiliation.

The second paper (Chapter 3) builds on the findings reported in the first paper, which highlight the demand for a better integration leveraging both the inter-building effect among buildings and occupants' interpersonal influence on energy conservation. This paper extends the knowledge by examining the synergy that may exist at the intersection between these "engineered" building networks and "social" peer networks, focusing specifically on the additional energy saving potential that results from interactions between the two effects.

The third paper (Chapter 4) presents a novel, cost-effective Energy Saving Alignment Strategy (ESAS) for multi-family residential buildings that seeks to align the indoor thermal preferences of each household with the thermal environment within their apartment. By placing each household in a housing unit that has a natural temperature that most closely matches their preferences, this strategy aims to obtain the combined highest level of thermal comfort satisfaction and the lowest space conditioning demand and thus the most efficient energy use.

Chapter 5 discusses the contributions of this dissertation to our current understanding of human-environment systems in the context of energy efficiency and sustainability. In Chapter 6, limitations of the research are discussed and potential areas for future research are suggested. Finally, a comprehensive bibliography is provided in the Reference Section.

Chapter 2

2. THE IMPACT OF PLACE-BASED AFFILIATION NETWORKS ON ENERGY CONSERVATION: AN HOLISTIC MODEL THAT INTEGRATES THE INFLUENCE OF BUILDINGS, RESIDENTS AND THE NEIGHBORHOOD CONTEXT

2.1 Abstract

Models that consider, separately, the energy use of networks of buildings and networks of building occupants have been explored in existing literature toward the goal of understanding the role of building networks or occupant networks on building energy conservation. Yet, the neighborhood surrounding buildings and their occupants can also have an influence on energy consumption patterns. Thus, the inclusion of this influence is important in an holistic evaluation of the built environment for aggregate energy performance. We developed an integrated, inter-building model comprised of a building network, an occupant social network, and the surrounding neighborhood facilities, to conduct a three-stage prediction of energy conservation potential for an assumed urban residential block. We inferred utilization of neighborhood facilities from U.S. Census demographic data and then applied affiliation network theory to deduce inter-building occupant affiliation networks, and thus predict the potential spread of energy conservation that might be achieved via a combination of social networks and eco-feedback systems for our assumed block. Our model results show that eco-feedback systems that leverage place-based social networks might lead to improvements in energy efficiency performance at the inter-building level that are comparable to efficiencies

gained through typical building retrofits.

2.2 Introduction

The reduction of energy consumption in the built environment is a key objective in many sustainability goals. Yet this issue is complex, because it is dependent upon three components: buildings, residents, and the neighborhood context surrounding those buildings and residents [47]. Furthermore, these three components are interconnected as residents interact with buildings, each other and their surrounding environment [48]. Traditional methods that focus on energy reduction in single buildings are often too narrow in their analysis and limited in their scope of impact to help achieve targets to reduce energy consumption of the built environment as a whole. In contrast, adopting an aggregate view at the inter-building level that systematically examines the aforementioned three factors—buildings, residents and their surrounding neighborhood—can highlight energy conservation strategies that could neither be revealed nor attained using an approach that considers only buildings or their residents [49].

Energy consumption among groups of buildings differ from the total amount of all single buildings because a building can impact adjacent buildings' energy use through, for example, shading and ventilation [31, 32, 47], among other effects. At such inter-building levels, research efforts to understand the aggregate effect of buildings on other buildings energy consumption patterns have been reported [4]. With respect to the residents of the buildings themselves, occupants' interpersonal connections can provide them with the incentive to consume less energy, due to information sharing and/or a motivation to keep up with peers who have adopted energy conservation practices. This interpersonal peer network effect on energy consumption has been observed and empirically supported in experimental studies [41,

42]. In studies examining environmentally conscious behavior at the neighborhood level, two factors were discovered that resulted in high participation in curbside recycling programs; namely, residents' concern for the environment and the pressure from neighbors and friends who participated early on in such programs [46]. Thus, examining the interpersonal relationship among building occupants is an important step to better understand the role of social networks on occupants' energy conservation behaviors, as well as other pro-environmental behaviors.

Surrounding the buildings and residents, the neighborhood context plays a critical role in the formation, resulting structure and strength of the aforementioned occupants' social networks, especially when examined at the inter-building level as opposed to within a single building. This is because places in the neighborhood provide locations in which interpersonal relationships with others can be developed, and people are attached to place-based social relationships [45]. Frequent walks through a neighborhood and the occurrence of encounters with others in a neighborhood contribute to a feeling of being at home, and individuals whose activities are organized around the same focus, such as membership of a neighborhood club, frequently become interpersonally connected over time [50].

Though buildings' mutual impacts and neighborhood contextualized occupant behaviors influence energy consumption, studies that attempt to evaluate the impact of these multiple effects and quantify potential energy savings to be gained from renovating buildings and leveraging occupant social networks derived from neighborhood affiliation are lacking. The study presented in this paper attempts to fill this gap. The sections of the paper are organized as follows. Section 2 describes the background and logic behind place attachment, social

networks, and environmental behavior as a foundation for linking building occupant social networks to neighborhood affiliations and openness to adopting pro-environmental actions. Section 3 describes the hypothetical urban residential block used for the study, specifies models and data for each stage of the methodology workflow, and introduces affiliation networks and artificial neural networks as analysis tools. The simulation results and analyses are presented in Section 4, while discussion and conclusions are provided in Section 5.

2.3 Background

Place attachment, or belonging, which deals with human bonding to the physical environment, is expected to convey social meaning associated with human-environment relationships [51]. Place attachment often develops through direct experiences with the neighborhood social and physical environments [52]. The higher the number of close neighbors and friends that are known and live nearby, the higher the attachment to the neighborhood and the greater the pride residents take in their neighborhoods [52]. Place attachment has been proven to influence both the perception of, and response to, actual changes in the environment [53]. Studies conclude that the higher the neighborhood attachment, the more likely individuals are to develop a set of norms [54] and exhibit care and concern for the place [55]. For example, empirical evidence has shown that place attachment predicted negative attitudes toward a major hydropower development among residents of a rural area in Norway, based on residents' concerns that the development would have a detrimental environmental impact [51].

In parallel to place attachment, place identity and environmental identification that generates social cohesion and satisfaction is, according to the City-Identity-Sustainability model, an important condition for ecologically beneficial behavior to occur [56]. Similarly,

Uzzell et al. [57] contends that socially cohesive communities that have a strong sense of social and place identity will be more supportive of environmentally sustainable attitudes and behavior, and provide some empirical evidence to buttress this theory. Furthermore, environmental citizenship, developed from active involvement within a community and a feeling of good community spirit, was also found to lead to recycling, characterized as normative behaviors, among household waste management practices [58].

Schools and churches have been particularly regarded by scholars as places that enhance community engagement and potentially lead to environmental citizenship of the neighborhood. Mesch and Manor [52] observed that, by and large, children played and socialized with their neighbors and usually attended school in the neighborhood: they concluded that this centrality of place in the socialization process increased the interest of families with children in the community in environmental stewardship, and nurtured local attachment. In an empirical study in Northern Ireland, Kurz et al. [59] found that the sense of community had a supportive effect on curbside recycling, and involvement in local community groups, e.g. church groups, contributed to a higher sense of community.

Human concern for the environment is generalizable by its definition as “both a specific attitude directly determining intentions or more broadly to a general attitude or value orientation” in a pro-environmental sense [60]. Analyses have shown that recycling behavior is positively correlated to energy and water conservation in terms of the usage of programmable thermostats, fluorescent lights, water-saving showerheads and low-volume toilets [61]. The study indicated that recycling might operate as a context, and a first step toward the adoption of other pro-environmental behaviors. Thus, people who adopt one pro-environmental behavior

are more likely to engage in other such behaviors. For the purpose of this research, we have therefore assumed that prior research citing relationships between places and pro-environmental behavior supports our supposition that neighborhood level, place-based relationships can support energy conservation behaviors among groups of residents. The goal of our study was to answer the question: how could leveraging place-based affiliation networks affect energy conservation performance at the inter-building level, compared to efficiencies gained through typical physical building retrofits?

2.4 Research Design and Methodology

To achieve our research goals, we integrated models for building and human networks to examine energy consumption dynamics in a hypothetical neighborhood block whose building occupants' social networks are formed at a neighborhood level. Our methodology flow chart, as illustrated by Fig.3, can be conceptually divided into individual building level and inter-building level analyses, respectively, as well as three stages operationally incorporating two models. The three barrel-shaped databases refer to where we run simulations and perform our primary calculations, while the two parallelograms represent external sources of empirical data.

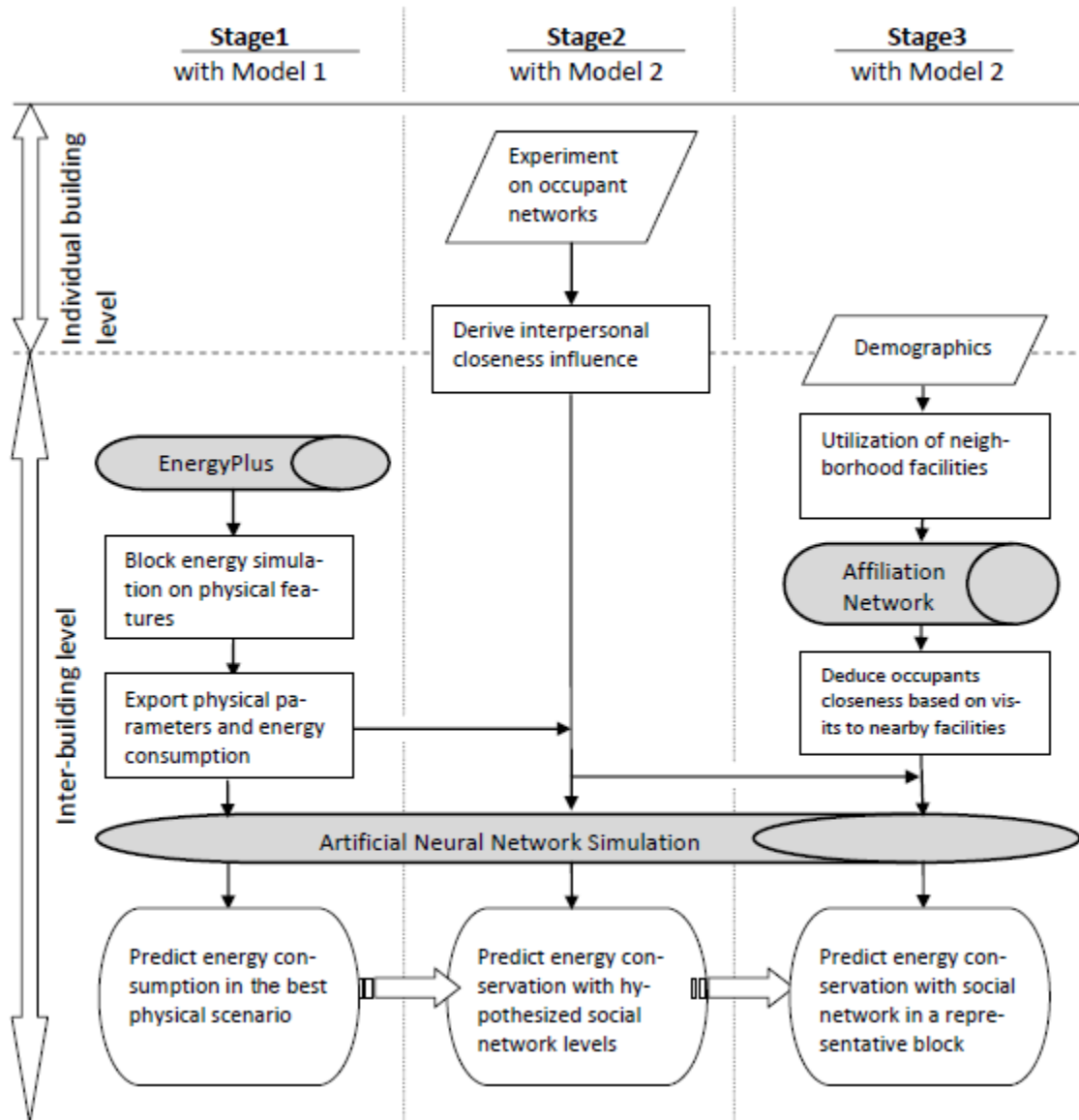


Figure 3. Research methodology flow chart

2.4.1 Stage 1: Predicted Energy Conservation with Physical Interventions

Urban Residential Block Description

We designed a “prototypical” American block of ten residential single-family houses of three different sizes (Fig.4) located at Albany, New York. This block and associated physical scenarios described in subsection 3.2.1 are modeled in other published works [4, 35]. Every

house has two floors: on the ground floor there is a kitchen, a living room, a connection area, and a bathroom. On the upper floor there are two or three bedrooms, a bathroom and another connection area. The architectural features of the buildings comprising the urban residential block were realistically designed with appropriate material and physical properties for the floors, external walls, internal partition walls and roofs. Every indoor thermal zone was described by specific occupant schedules that associate appropriate internal gain values to human body functional activities, lighting, hot water needs, personal computer use, cooking appliances, etc. [4].

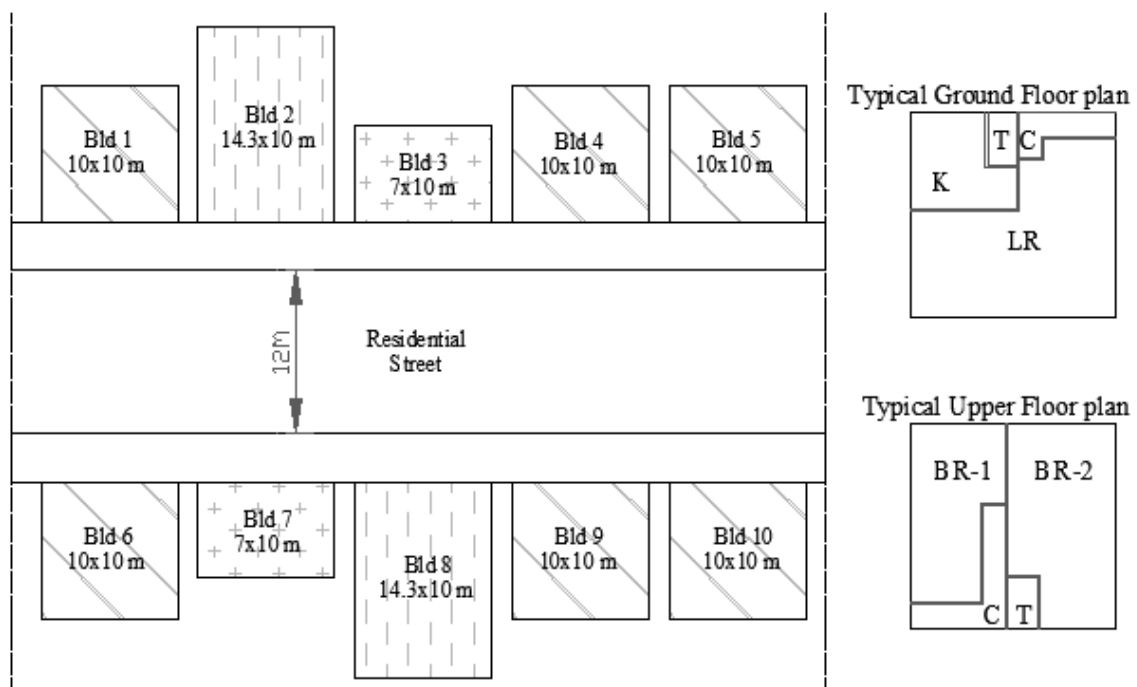


Figure 4. Urban residential block modeled (plan view)

Physical Scenarios and Optimization

The building network energy efficiency assessment from a physical standpoint was used as the

starting point for the research. Specifically, we examined an urban residential block to understand the impact of surrounding buildings on the energy consumption profile of an individual building. To fully account for the inter-building effect within the group of buildings, we simulated the block as a whole, instead of a single house or a single room in a house.

The building simulation program EnergyPlus, which is a simulation program provided at no cost by the U.S. Department of Energy, was used to forecast the inter-building energy demand across various windows and building envelope scenarios. These scenarios considered properties such as the U-value and solar heat gain coefficient (SHGC), which are known to significantly impact building cooling and heating loads. Two groups of different scenarios were studied (Table 1) with scenario 1 representing the base case scenario: the first group (2, 3) focused on window types with different SHGC and U-values, while the second group (4-6) focused on the influence of adding insulation layers of different thicknesses.

Table 1. Scenarios characterization

Scenarios	Windows	Walls
1	Single glazing, 6mm, clear (SHGC=0.81, U-value=5.778)	No additional insulation (U-value=0.314)
2	Double glazing, 3mm+13 air+3mm (SHGC=0.761, U-value=2.556)	No additional insulation
3	High performance double glazing, 6mm LoE+13 mm argon+6mm clear glass (SHGC=0.568, U-value=1.761)	No additional insulation
4	Base case glazing	Insulation XPS extruded polystyrene, 4cm (U-value=0.200)
5	Base case glazing	Insulation XPS extruded polystyrene, 8cm (U-value=0.162)
6	Base case glazing	Insulation XPS extruded polystyrene, 12cm (U-value=0.136)

*U-value in $W/(m^2K)$

We compared all of the physically based scenarios in terms of energy demand (Table 2).

Summing the total year round energy consumption, we found that our selected physical modification strategies forecast energy reductions, in comparison to the base case scenario, ranging from 2.3% to 22.3%. Specifically, the most energy efficient scenario 3 consumed 22.3% less energy for the whole year than the base case scenario 1, with a pronounced saving of heating consumption in winter. Because scenario 3 represented the physical set-up with the greatest potential energy savings, we adopted it to explore how inter-building human networks might further contribute to the block's overall energy conservation.

Table 2. Scenarios energy consumption (MWh)

	s1	s2	s3	s4	s5	s6
Room Electricity	30591	30289	30289	30289	30289	30289
Lighting	30711	31008	31008	31008	31008	31008
Heat Generation (Gas)	159136	115062	106656	153993	151861	150415
Chiller (Electricity)	19467	21223	17236	19685	19825	19925
Domestic Hot Water	8604	7792	7792	7792	7792	7792
Total	248509	205374	192981	242767	240775	239429

Model, Variables and Artificial Neural Network Model Construction

To predict energy consumption in our building network based on physical attributes, we used model 1 (see Fig. 3) as expressed in Eq. (1).

$$E = f(T_{op}, T_{out}, Solar, Occup) \quad (1),$$

where E represents energy consumption in kilowatt hours, which is the sum of cooling, heating, hot water, lighting and other room electricity usage. All data are exported from EnergyPlus (EP).

We applied an artificial neural network (ANN) to satisfy the predictions of equation (1).

ANNs are computational tools that can be trained in complex causal relationships among numerous factors and used in many fields for prediction. Researchers have applied ANN methods to forecast energy consumption [19, 20], energy savings from both building and equipment retrofits [21, 22], as well as other performance parameters [23]. Based on its successful application in modeling non-linear energy consumption under various socio-economic conditions [18] and its efficient simulation time [62], we selected ANN as the simulation tool for this study.

A multi-layer feed-forward neural network was constructed using a log-sigmoid transfer function and a linear transfer function for the hidden layer and output layer, respectively. The most widely applied back-propagation training algorithm [63] was adopted with a learning rate of 0.1. The entire dataset was divided into a training set, a validation set, and a test set, with each containing 50%, 25%, and 25% of the total.

Note that summer and winter seasons have disparate energy use patterns: summer exhibits a balanced pattern among all forms of energy use, i.e., cooling, heating, lighting, hot water, and room electricity; while heating dominates all other four forms of energy use in winter (refer to Table 2). The presence of every form of energy use is necessary for retaining the comprehensiveness of the ANN model as well as the generality when applying the trained ANN model to other places with moderate climates not as extreme as Albany, so we chose the summer and part of the intermediate seasons (May 1 to September 30) as the study period for ANN prediction. Note that this prediction period choice for later stages in the study is independent from the optimal physical scenario selection in Stage 1. Each of the variables is a vector of 3,672 hour-by-hour elements during the study period for the most year round energy

efficient scenario s3 as found in this section, using typical weather measurements in Albany, New York. The physical meanings of the variables are stated in Table 3.

Table 3. Description of variables

	Variable	Description
Dependent variables	E: energy consumption[kWh]	Energy consumption= cooling consumption + heating consumption+ hot water consumption + room electricity and lighting consumption
	Cooling consumption [kWh]	Energy that indoor environment needs to obtain and maintain thermal target in summer.
	Heating consumption	Energy that indoor environment needs to obtain and maintain thermal target in winter.
	Hot water consumption [kWh]	Energy that indoor environment needs to produce the necessary hot water amount for human activities.
	Room electricity and lighting consumption [kWh]	Electricity that indoor environment needs to keep up all the electric supplies for occupants' activities and for lighting system.
Independent variables	T _{op} : operative temperature [K]	Indoor operative temperature. Average values within the free running buildings.
	T _{out} : outdoor temperature [K]	Outdoor dry bulb temperature. Typical of the considered site weather (Albany, NY).
	Solar: solar gains [kWh]	Short-wave solar radiation transmission through all external windows, varying with time and weather.
	Occup: occupants gains [kWh]	Sensible gain due to occupants related to activities schedules.

2.4.2 Stage 2: Energy Prediction with Hypothesized Social Networks

Model 2 (see Fig. 3) was used to predict further energy conservation under the added influence of the human networks that occupy the buildings, as expressed in equation (2).

$$E = f(T_{op}, T_{out}, Solar, Occup, closeness\ index) \quad (2)$$

The “closeness index” data in Stage 2 is derived from one of a series of experiments from November 2009 to March 2010 conducted in a Columbia University urban multistory

residential dormitory [41, 42]. The researchers conducting this study used logistical regression to demonstrate that network degree was positively correlated with statistically significant reductions in a building occupant's electrical consumption, provided that occupants were provided with eco-feedback information that contextualized their usage with respect to that of their peers [42]. Network degree was measured as the number of peers included in a given occupant's participants' energy use profile. The closeness of the relationship among peers was self-identified by occupants as "no relationship", "acquaintance", "friend", or "close friend" [42]. Ratings of 0, 1, 2 and 3, respectively, were allocated to each of these indicators. For the purpose of our research, we defined closeness index (CI) as the summation of these ratings for each occupant throughout his/her peer network, and assumed that an occupant's CI could serve as a proxy for the strength of ties between occupants in a social network. Because there were 42 occupants in the study group, the maximal possible CI for each occupant was $3 \times 41 = 123$. However, based on their reported relationships during the study period, the actual range of the CI for the occupants in the Columbia University dormitory was between 0 and 16. To link CI to potential energy savings, we defined the energy savings of each occupant as the percent difference between the occupant's daily average electrical consumption during the pre-study baseline period, and that during the experimental period itself. For double occupancy rooms, we used the average electrical consumption for each occupant. A regression of energy savings on CI over the range [0, 16], returned a savings of 3.45% for each increment of CI, with a significance level of $p < 0.05$. We adopted this relationship between CI and energy savings for our model, recognizing the limitations of this decision. Specifically, the model is based on data obtained from a study of university students housed in an multi-story residential building, and

might not apply to the occupants of the residential block which are the focus of the work presented here. Nonetheless, the fact that the model is based on data from an actual study is considered important. Furthermore, in the absence of any published alternative, it is also considered adequate for this first-time examination into the influence of place-based affiliation networks on energy conservation at the inter-building level.

We use the closeness index in both the individual building level network and inter-building level network analyses. We analogously compare each household to each other household in the block, as we compared each occupant to each other occupant in the urban residential building. We assumed that the scenario of “close-friend”, although possible for the student occupants of the residential dormitory, was unlikely for the occupants of our urban residential block. Thus, we excluded the “close friend” category (a rating of “3” in the dormitory study) from our analysis of the residential block.

Because our urban block consists of 10 houses, each house has 9 potential connections, with each potential rating from 0 to 2 as relationship closeness, because we deliberately excluded the rating of 3. Thus, altogether, each house’s CI in the network ranges from 0 to 18. Uniformly random numbers on [0, 18] were generated as CI, the variable ‘E’ for model 2 was adjusted by Eq. (3) from ‘E’ in model 1 and served as the updated energy consumption in kilowatt hours.

$$E(\text{model 2}) = E(\text{model 1}) * (1 - CI * 3.45\%) \quad (3)$$

2.4.3 Stage 3: Energy Prediction with Place-based Social Networks

Affiliation Network Modeling

Although in empirical studies place-induced social networks have been shown to exist that

could potentially engender energy-conscious behavior within members of the network, none of these studies has resulted in models that quantify the strength of social networks based on the characteristics of a neighborhood. To overcome this limitation, we utilized affiliation network theory to estimate the strength of neighborhood place-based social networks for the inhabitants of our hypothetical residential block.

The term “affiliations” refers to membership or participation data, which can be represented as mathematical graphs in which nodes correspond to entities and lines correspond to ties of affiliation among the entities [64]. Affiliation graphs are distinctive in having the property of bipartiteness, which means that the graph’s nodes can be partitioned into two classes, so that all ties only occur between classes but never within classes. Generally, one entity is people and the other is gathering situations, and a tie between them is formed if the former is “a member of” or “participates in” the latter. The realm of activities includes being part of an organization, neighborhood, frequenting a place, pursuing a hobby, etc. For example, a classic affiliation dataset collected by Davis et al. [65] recorded which women attended which social events in a small southern town.

In some cases, the purpose of collecting affiliation data is not to understand the pattern of ties between two sets, but to understand those within one of the sets. Some kind of tie among members of a node set can be constructed by defining co-affiliation (e.g. attendance at the same places) as a tie [66]. When shared between two people, activities tend to increase the likelihood that they will interact and hence form a link in the social network [67]. Altogether, the affiliation network solves the question of how to represent the set of activities a person takes part in, and how these affect the formation of social network ties. The use of affiliation network

theory therefore provides a way to reconcile differences between social networks developed between the student occupants of the residential dormitory, whose behavior was used to develop the model linking CI to energy savings, and the residents of the urban block studied here. Specifically, the two contexts can be similarly treated as linked communities where social norms and levels of CI within each network can motivate both private and public actions, by informing individuals of what is likely to be effective or adaptive behavior in a given situation [68].

Data and Method

With the purpose of accurately quantifying the occupants' social network based on utilization of neighborhood facilities, so as to map the social network behaviors in a single building onto behaviors more relevant to our urban block scenario, we derived the affiliation network from demographic data for a block located at Albany, New York. We obtained these data from U.S. Census Bureau and Association of Religion Data Archives (ARDA). We extracted relevant statistics from the census data as follows: (1) average household size is 2.54; (2) 45% of the families have children; (3) approximately 100% school enrollment for children under 18; and (4) 27,044 of the children attend elementary schools (grades 1-8) while 16,560 attend high schools (grades 9-12). Thus we deduced proportionately that in the 10 households in the block, 5 families consist of 2 adults and 1 child, the other 5 families consist of only 2 adults; 3 children attend elementary school while 2 children attend high school. The ARDA archives also revealed that the Catholic church adherence rate is 47% in New Albany whereas other kinds of church adherence are relatively negligible, where "adherents include all full members, their children, and others who regularly attend services". Thus we assigned 5 households in the

block as attending church service. Altogether, we identified the gathering places that the building occupants would encounter in their neighborhood as elementary school, high school, and church. We then translated these assumptions to an affiliation network. Figure 5 displays one realization pattern conforming to the above deduced proportions of schools and church attendance. Equivalently, we transform this two-mode graph to a matrix A with households as rows and places as columns to be used for further calculation (Table 4).

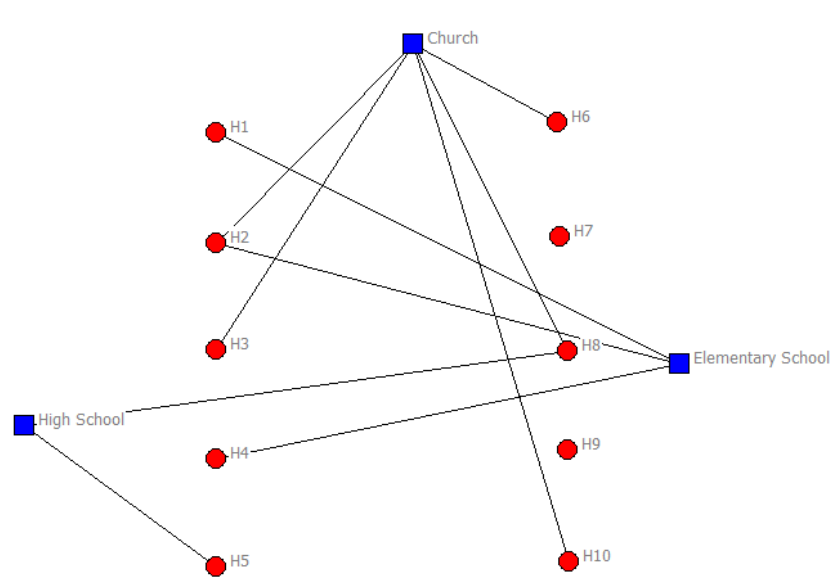


Figure 5. Houses-by-places graph

Table 4. Two-mode house-by-place matrix

	ES	HS	C
H1	1	0	0
H2	1	0	1
H3	0	0	1
H4	1	0	0
H5	0	1	0
H6	0	0	1
H7	0	0	0
H8	0	1	1
H9	0	0	0
H10	0	0	1

2.5 Results and Analysis

2.5.1 Energy Use Prediction under Best Physical Scenario in Stage 1

This subsection presents the predictive results of Stage 1, where the variables of model 1 under the most energy efficient scenario (s3) are used to train the neural network. The energy consumption for a typical week in summer (August 19th to August 25th) based on the optimal physical scenario determined on a year round basis is displayed in Fig.6, while the validation of the ANN model for the entire dataset is shown in Fig.7.

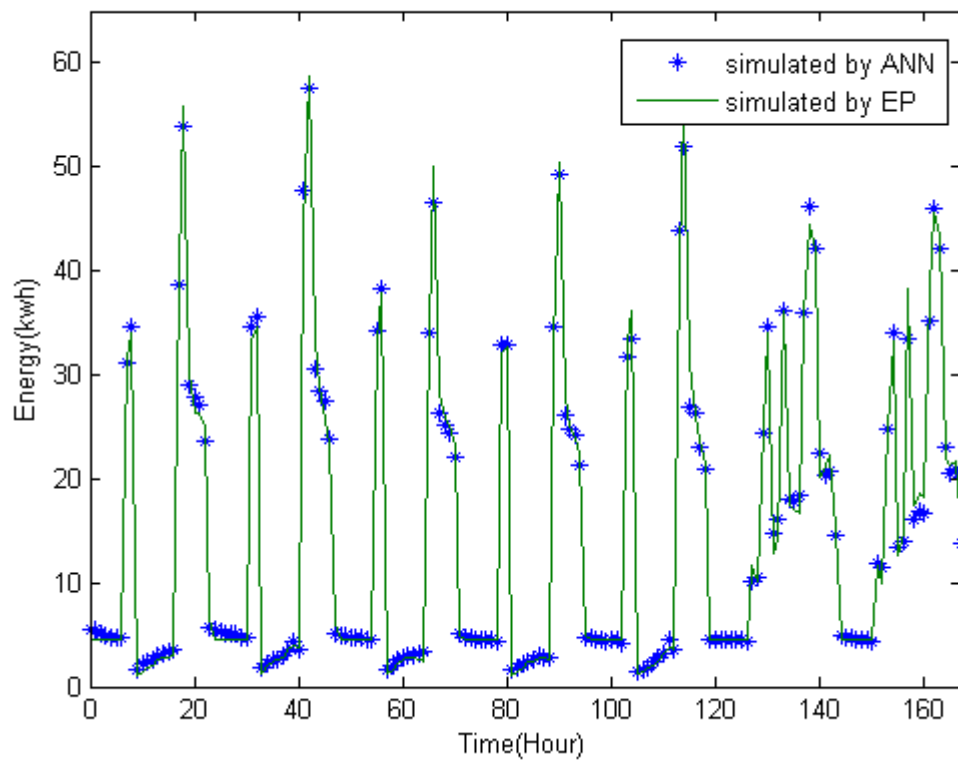


Figure 6. Energy consumption under scenario 3

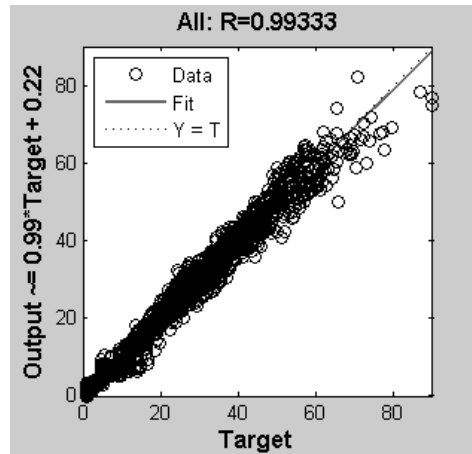


Figure 7. Validation of model 1

Both figures support the validity of the simulation results of the artificial neural network. In Fig.6, the majority of the energy consumption points predicted by ANN coincide with vertices of the plotted line, which are the prior measurements of energy consumption simulated by EP. The percentage difference between the predicted values and previously simulated values is 0.16%. The first five days of the week have a different consumption pattern than the last two days, which is explained by disparate occupant schedule settings for weekdays and weekends. In Fig.7, predicted output points from ANN are plotted against their targets, i.e., prior simulated results from EnergyPlus. The entire dataset approximately falls along a 45° line, verifying the proximity of the output and target values. Altogether, the correlation coefficient R between the ANN output and target values is high at 0.9938. These two figures justify the correctness of Eq. (1), i.e. the independent variables' prediction power of the energy use.

2.5.2 Energy Conservation Prediction under Hypothetical Social Networks in Stage 2

As changing physical features results in higher energy efficiency as discussed in Section 2.4.1, introducing an interpersonal closeness index into the network in Stage 2 will lead to further energy conservation. Block energy consumption for a typical summer day for the three social

network closeness levels of “no relationship”, “acquaintance” and “friend” is shown in Fig. 8 (the curve marked with “derived relationship” is drawn from Stage 3 and will be discussed in Section 2.5.3). The validation of the ANN prediction for the entire dataset is shown in Fig. 9. Supported by a correlation coefficient of 0.9916, the neural network incorporating the human closeness index is well trained and provides strong predictive capability.

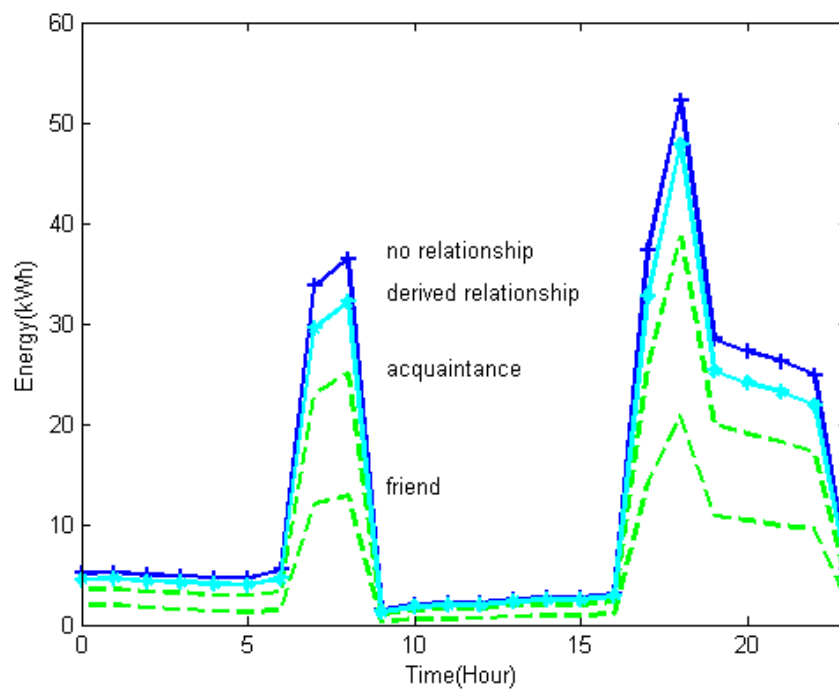


Figure 8. Energy consumption under human networks

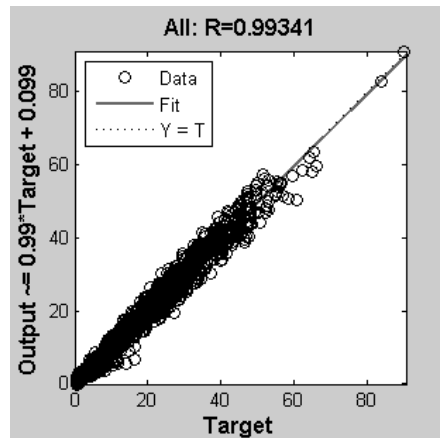


Figure 9. Validation of model 2

Figure 8 was derived with the following human network settings:

- each family has “no relationship” with the other nine families, thus CI for each family is 0;
- each family is an “acquaintance” of the other nine families, thus CI for each family is 9;
- each family is a ‘friend’ with the other nine families, thus CI for each family is 18.

There are numerous intermediate closeness levels between the no-relationship and all-friend levels, but only the three network constructs are displayed here for simplicity. The shape of each line has a trough between 9 am to 4 pm, which results from the occupant schedule setting, which assumes people are generally out of their homes during the day on weekdays.

An increment from each level of interpersonal networks to the next closer level will lead to an energy conservation of approximately $3.45\% \times 9 = 31.05\%$ when an intervention, which was the eco-feedback system in the dormitory study upon which our model is based, is introduced

(see Fig.8). Such energy saving potential is possible when interventions that promote energy saving behaviors and leverage building occupant social networks are introduced. A previous study found that occupants who had access to real-time energy feedback showed a 55% reduction over the 2-week period [69], which serves as an external validation of the percentage obtained in this study. Of interest is that fact that the magnitude of savings that can be realized through leveraging networks of “friends” is higher than that predicted by EnergyPlus for the most efficient scenario s3.

2.5.3 Results of Stage 3

Derivation of Place-based Affiliation Networks

Starting from the affiliation network example matrix A in Figure 5, we performed the multiplication AA' to yield the one-mode house-by-house matrix P , where each off-diagonal cell is the total times that a pair of households both visit the same place and each diagonal entry is the total times a household visits one of the neighborhood facilities, as implied in Eq. (4).

$$P_{ij} = \sum_{k=1}^n A_{ik}A_{jk} \quad (4)$$

By co-affiliation theory, this number is an indicator of the strength of the tie between two households. In order to adopt this number as a proxy for social ties, we first normalize it by a well-known approach that uses the Jaccard coefficient (denoted J) [70]. Specifically, J is the number of events attended in common by a pair of people or households as a proportion of events that are “attendable”, as determined by the fact that at least one of the two people/households attended the event. With the Jaccard coefficient, we were able to classify the friendship category according to the Jaccard Coefficient range, and derive the place-based affiliation network (Table 5):

- If $J=0$, relationship=0, representing no relationship
- If $0 < J < 1$, relationship=1, representing acquaintance
- If $J=1$, relationship=2, representing friend

Table 5. One-mode house-by-house positive relationship matrix

	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10
H1	0	1	0	2	0	0	0	0	0	0
H2	1	0	1	1	0	1	0	1	0	1
H3	0	1	0	0	0	2	0	1	0	2
H4	2	1	0	0	0	0	0	0	0	0
H5	0	0	0	0	0	0	0	1	0	0
H6	0	1	2	0	0	0	0	1	0	2
H7	0	0	0	0	0	0	0	0	0	0
H8	0	1	1	0	1	1	0	0	0	1
H9	0	0	0	0	0	0	0	0	0	0
H10	0	1	2	0	0	2	0	1	0	0

Then, we sum elements of each row to compute the closeness index for each household, and take an average to produce the CI for the block. For example, the computed CI for the network pattern shown in Table 5 is 3.6. Conforming to the same attendance proportion, there are altogether 5 other patterns due to different household-place combinations that are simulated to generate CIs of 2.8, 3.0, 3.2, 4.4, and 4.6, respectively. The overall average CI weighted by the probability of the occurrence of these six cases is 3.4, meaning that on average every household is acquaintance to 3.4 other households in the block, or is a friend with another household while being an acquaintance with 1.4 other households, etc.

Energy Conservation Prediction Under Derived Place-based Affiliation Networks in

Stage 3

As shown in Fig.8, the energy use reduction under the “derived relationship” using the average

CI fall between the range of no relationship and all-acquaintances, being closer to the “no relationship” level. This reveals the interpersonal closeness of the representative block as being close to a situation where only a few occupants are acquaintances. Because the derived social network arises from real demographic data, we hypothesize that the actual energy use reductions would likely be close to this average prediction. Thus, this figure illustrates the potential energy conservation that might be achieved by capitalizing on the strength of social ties and networks within a neighborhood as determined by neighborhood affiliations.

Figure 10 displays the detailed energy consumption for each of the six patterns of place frequenting and their weighted average during a typical summer month. Though the usage is largely influenced by weather conditions as simulation inputs, the relative reduction because of closer networks is revealed by the shaded area on the top of each bar. The deviation of different cases is small, with all data points closely gathered around their average. The sequence of cases follows the legend from top to bottom. The centralized result indicates that, as long as the attendance/visitation rate at a neighborhood site is predefined from demographics, the various realization of place-based affiliation network design will not bring unacceptable noise. With the precision of our approach justified, we expect the block energy saving of approximately 11.7% to reflect the role of neighborhood context in a world where such closeness is harnessed to invoke energy efficient behaviors. This savings is at approximately the same level as the physical retrofit scenarios described earlier which resulted in 2.3-22.3% less energy being consumed.

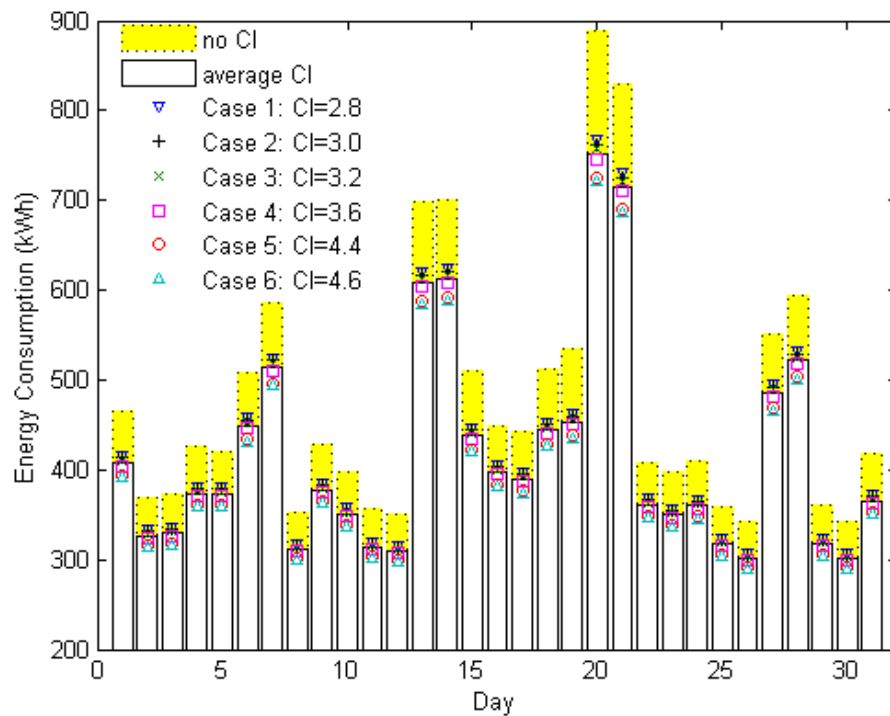


Figure 10. Reduced energy consumption under derived human network (average and deviations)

If we were to integrate the physical and human stages, the block shows a potential of consuming $1-(1-22.3\%)\times(1-11.7\%)=31.4\%$ less energy when it has a normal social and affiliation network close to the derived one and there is energy efficient physical design of the block through the typical interventions considered in EnergyPlus (taking a baseline block scenario in which none of the residents influence each other's energy consumption). Leveraging such social networks for energy conservation behavior through interventions such as eco-feedback systems can achieve a roughly equivalent energy saving effect to a typical energy conserving physical retrofit.

2.6 Discussion and Conclusions

This study answers the question of how could leveraging place-based social network affect energy conservation performance at the inter-building level above and beyond efficiencies

gained through typical building retrofit. We drew from earlier research that modeled a physical building network of a typical urban residential block of homes, and calibrated our data using demographics and an experiment that examined the role of peer networks on energy consumption in an urban residential building. We then built a place-based social network using an affiliation network approach, and applied artificial neural network methods to examine the impact of integrating buildings as physical and social networks that influence energy consumption situated in neighborhood context. Our results show that, compared to the baseline case where residents do not influence each other's energy consumption, the residential block has a potential for consuming 2.3-22.3% less energy when renovated with typical energy efficient physical design, and an additional potential for saving 11.7-31.1% energy if interpersonal closeness is leveraged for encouraging energy conservation behavior.

Theoretically, we established a holistic model to evaluate built environment energy efficiency performance that consists of three components: building networks, occupant social networks, and the surrounding neighborhood facilities. This is the first such study to model all three components holistically together. We consolidated the logic chain that place attachment and identity from frequenting neighborhood facilities can generate social networks among occupants, the closeness of which will encourage pro-environmental behaviors. Specific for the two latter components, we developed a novel procedure to deduce social network among occupants living in a particular neighborhood using U.S. census and religion survey data. The idea behind our analyses was to produce a nuanced strength of interpersonal ties from utilization of community facilities so as to realistically embody the neighborhood facilities' effect on occupant social network.

We also replicated and expanded an EnergyPlus procedure using a more efficient ANN with a drastic simulation time reduction from approximately an hour to seconds. Accordingly, hourly energy consumption series were obtained for multiple occupant network closeness settings. All ANN models achieve as high as 0.99 correlation coefficients between the predicted and target value for the entire dataset, statistically supporting the our quantitative conclusion.

Our research suggests that social networks among residents should be harnessed by community planners in inter-building level energy management beyond physical green design to achieve the highest energy efficiency. This is because of the larger unexploited potential saving impact of harnessing a close social network beyond physically efficient buildings, and also because such encouragement of energy conservation might be more cost-effective than physical renovations. Thus we should on one hand, further enhance the interpersonal closeness among residents, and on the other hand, carry out energy saving interventions that make use of such social networks. As a means for the former, including more shared spaces where neighboring occupants may interact might be effective, since it utilizes neighborhood facilities' influences on social networks. For the latter, it is worth noting that long-term pro-environmental behavior strategies have to be located in the relationships that exist between people in the community and the relationship between those people—individually and collectively—and their environment [57]. Correspondingly, to motivate residents to conserve energy, making them aware that their neighbors and friends are changing in similar ways is known to be effective [71]. To leverage such interpersonal relationships, we suggest community-based social marketing to promote energy conservation in homes. Behavioral

feedback, either on monthly energy bills or real-time, and incentives are workable ways, particularly among which, shared energy monitoring systems has been proved to be impactful [72]. When combining behavioral feedback with subsidies for retrofits, hybrid programs can yield greater energy savings per home [73].

The accuracy of this study's quantitative results is subject to the quality of the residential experiment data and availability of relevant demographics. In this research, only schools and a church were identified as the neighborhood facilities that enhance social and place-based affiliation networks. Given new datasets, other places, e.g. playgrounds and sports fields, may be introduced to the model, consequently creating more communication opportunities among occupants and strengthening the derived social network. Another limitation of the study is that the dorm residents might not behave in the same way as the household residents and that the range of CI is not exactly the same for the two situations, but the analogy is sufficient for the purposes of this initial attempt to examine the potential role of place-based affiliation networks on neighborhood energy conservation.

In light of future research, researchers should focus on the occupant behaviors situated in the neighborhood and the accompanying social network context. According to Mosler [74], environmental problems are not actually problems between people and the environment but rather problems among members of a social system. Empirical studies are recommended to reflect the effect of place-induced affiliation networks among residents on energy conservation in real neighborhoods, by means of surveys or residential experiments. Modeling the dynamics of the place-attendance process together with the evolution of social networks might help to better understand environmental attitudes and behavioral changes, and eventually energy

reduction in progress. Future research is also suggested to adopt a holistic network perspective of urban residential buildings, networks of individuals that occupy them, and particularly surrounding factors that may interact with the former two components. Such a view is advantageous to pursue better aggregate energy efficiency and reduction in greenhouse gas emissions.

Chapter 3

3. NETWORK SYNERGY EFFECT: ESTABLISHING A SYNERGY BETWEEN BUILDING NETWORK AND PEER NETWORK ENERGY CONSERVATION EFFECTS

3.1 Abstract

Researchers have demonstrated that network effects on energy consumption exist when buildings are examined within physical networks (i.e. they exhibit an inter-building effect) and when individuals influence the energy use of their peers (i.e. a peer network effect is present). However, any synergy that may exist between these two effects from which greater aggregate energy savings can be achieved remains unexplored. To examine this potential synergy, we simulated a residential block in EnergyPlus and analyzed the impact of two retrofit options. We identified a case where the less energy efficient option for a single house produced higher efficiency in the neighboring houses. We then conducted a survey of homeowners that asked them to make a decision between such retrofit options. Our results reveal a phenomenon that knowledge of the impact of the two retrofit options on each building combined with strong personal relationships between the homeowners can drive decision-making toward aggregate optimal outcomes. These outcomes resulted in energy savings that were greater than the sum of the energy saving potential when either one of the conditions was individually satisfied. We conclude by defining this additional energy saving potential at the intersection between the two effects as the network synergy effect.

3.2 Introduction

Reducing energy consumption in the building sector is an urgent priority. The emphasis of research on energy consumption and the implementation of strategies to increase energy efficiency largely focus on the energy use of individual buildings. However, interventions designed to decrease the energy consumption of one building can have a significant impact on the thermal environment of neighboring buildings, which varies given the spatial relationships of the buildings and the surrounding urban morphology [4, 35]. The full potential for energy reduction, therefore, may require examining energy consumption and conservation for a group of buildings. Such optimization can be achieved with the goal of better network-wide energy performance through, for example, harmonized architectural and technical design or coordinated electricity consumption. On a much larger scale, the urban heat island phenomenon exists in part because of relationships between buildings and climate, which indicates that a more holistic view of thermal energy dynamics consider a network of buildings situated in its local environment.

In addition to lost energy savings due to decisions made based on a single-building view, an energy-efficiency gap exists between the optimal and actual energy use [5]. Electricity use continues to increase despite many advanced energy efficient building practices and retrofits. A rebound effect has been observed as consumers' increased use of energy services is induced by the reduction in energy costs afforded by more efficient appliances and/or technologies [6]. A rebound effect may also occur when consumers increase their energy demand because they are satisfied with the improved thermal quality [75]. These negative impacts of individual consumer behavior regarding building renovation lead to an overestimated potential energy

saving based on purely technical calculations.

Besides the impact that individual decisions have on building renovation, individuals' interpersonal relationships within their peer networks can have a positive impact on energy conservation [41], which may offset this energy efficiency gap. This peer network effect is driven by the dissemination of pro-environmental behaviors [59]. Leveraging the social dynamics of occupants' peer networks may significantly increase aggregate energy conservation in their communities and is thus an important focus of research.

Previous network approaches to reducing energy use have primarily focused on: (i) reducing energy use at the inter-building level and mitigation of the ensuing environment stress, and (ii) leveraging interpersonal relationships among residents to improve energy efficiency. In particular, researchers found that the energy saving potential from the latter was at approximately the same level as the former [9]. Furthermore, greater energy savings may be able to be achieved when both approaches are adopted [49]. However, considering the interactions between residents and buildings and between residents and the local environment [48], the aggregate saving may not be the sum of the impact of the individual measures because calculation of the aggregate saving may be dependent on the interactive effects of the two effects [47, 76]. We need research at the intersection between these two approaches to ascertain this. In this paper we examine whether such a synergy can exist where the impact on energy savings is greater if both the peer network and the inter-building effects are known to homeowners making an energy efficiency retrofit decision.

The sections in the paper are organized as follows: Section 2 describes current studies on buildings, occupants and their interaction; Section 3 contains a description of the simulation

and survey methods employed; Section 4 summarizes the network synergy effect results, which capture the choices made by homeowners when presented with the simulation test case scenario; Finally, in Sections 5 and 6, we discuss the implications of our findings, provide guidelines for future research, and discuss limitations before providing concluding remarks in Section 7.

3.3 Background

3.3.1 The Peer Network Effect

An individual's energy consumption depends on various personal and social factors including lifestyle choices and socioeconomic incentives. For example, the impact of lifestyle on current and future energy demand in European countries has been evaluated and income, labor time and composition of consumption associated with different household types were all found to be influential factors that explain patterns in an individual's energy use [77]. Research that has studied the adoption of one or more intervention strategies on residents' behaviors has observed a reduction in energy consumption [38]. More specifically, providing residents with feedback on their energy consumption has been shown to be an effective means of reducing their energy consumption [78].

However, studies have found that emphasizing personal determinants like values, attitudes, and personal norms over social norms can bias conclusions about energy saving [79]. Thus, solely focusing on residents as *individuals* may hinder the potential of fully mobilizing residents for greater conservation. In contrast to focusing on the behavior of individuals, some researchers emphasize the social aspects of behavior, particularly the interpersonal structure of relationships. This line of research assumes that the diffusion of a new technology or related

practice is communicated effectively through interpersonal channels among the members of a social system [80]. In other words, this *peer network effect* (PNE), i.e., an effect that reflects cases when peers imitate or influence the behavior of other peers, is a primary facilitator of the diffusion process.

The PNE on energy consumption has been observed and empirically supported in an experimental study [41]. In that study, the researchers found that within three days after initial access to electricity use information, the group of residents that were provided with their own and their peers' usage consumed a statistically significant 34% less energy than the control group. The energy consumption of another group of residents that was provided with only individual usage did not significantly differ from the control group. In other words, the energy saving norm embedded in the social network was observed to play a significant role in the energy savings that were encouraged by the feedback mechanism. Another study on hotel towel reuse concluded that conservation can be more attractive when framed as being in compliance with a more proximal social norm, which highlights the influence that an individual's close social relationships have on their adoption of conservation behaviors [81].

3.3.2 The Inter-Building Effect

The above studies support the importance of the PNE, i.e. that individuals influence the energy use of their peers. In addition to the PNE, researchers have also described how an *inter-building effect* (IBE) can influence energy consumption because buildings located close to one another can exert a mutual influence on thermal dynamics.

The energy consumption attributed to individual buildings has been extensively explored. With the goal of understanding how to optimize the energy efficiency of an individual building,

the energy consumption of buildings is generally evaluated by describing indoor thermal behavior, energy consumption, and building envelope features [15, 24]. More recent studies have begun to investigate the relationship between buildings and occupants by characterizing the building's energy performance relative to the occupants' behavior [25] and the typical occupancy schedules in each thermal zone [26].

To fully explore the potential for energy efficiency in the building sector beyond the interior thermal dynamics of a single building, some scholars propose a whole-building energy design concept [27], which is supported by research on energy modeling and simulation [28]. These advanced assessment procedures allow researchers to study the thermal behavior of realistic buildings under a variety of boundary conditions starting from the early design phases [29]. Using these procedures, several researchers have found evidence that the environmental stresses typical of the local environment surrounding a building may have a large impact on a building's energy assessment [30].

However, there are still large gaps in our understanding about the role that the local environment plays in terms of a building's thermal dynamics. For instance, research on groups of buildings is limited, where the main research thrust is focused on how mutual shading impacts adjacent buildings. The important effects of shading design were recognized by Olgyay in 1957 [33]. Thereafter, in a study on solar radiation, the mutual shading of co-located buildings was found to significantly vary the thermal conditions of the two buildings [34]. Then, a method embedded in a CAD tool was developed to quantify the impact of mutual shading between buildings and other objects like trees [36, 37]. In these studies, the effect of external elements on building energy performance has been assessed, in particular with respect

to the collection of solar energy.

Not only do buildings affect the thermal dynamics of other buildings, but buildings and the local climate mutually influence each other. The *urban heat island* (UHI) phenomenon reflects how buildings and other infrastructures impact meso-climate, which can in turn influence the buildings' thermal conditions. Researchers have defined the UHI as the temperature difference between a city and its surrounding rural area [82]. Some studies have examined the influence of UHI on the microclimate of urbanized areas [83]. For example, the impact of the ambient temperature rise due to urbanization or the impact of global warming on energy consumption was estimated in Hong Kong such that the electricity consumption could increase by 9.2% in domestic sector for a 1 degree C ambient temperature rise [84]. Thus, this research demonstrated that fluctuations in the local thermal conditions contribute to an IBE.

As the research to date has demonstrated, the mutual shading of adjacent buildings and objects can directly impact the energy use of other, proximal buildings. Moreover, changes in local climate indirectly impact broader-scale energy consumption attributed to buildings. A recent work proposed a systematic metric to evaluate their combined effects by simulating a group of buildings in EnergyPlus [4].

3.3.3 Motivating the Network Synergy Effect

The integration of occupant and building networks is firmly rooted in extant literatures. As an early foundation, Stern presents a conceptual framework for pro-environmental consumer behavior, emphasizing the determining roles of the interactions between personal and contextual factors [43]. He implies that consumer behavior is highly situational, and the extent to which behavior is mutable in the personal domain depends on the strength of contextual

forces. Guagnano proposes an ABC theory, where behavior (B) is an interactive product of personal-sphere attitudinal variables (A) and contextual factors (C) [85]. According to this theory, attitudes lead to changes in behavior only if contextual variables provide favorable incentives, and at a minimum, do not provide adverse incentives. Experimental studies have suggested that incentives are effective in reducing household peak electricity usage [86].

In exploring the energy consumption for a group of occupied buildings, the full context of an occupant's behavior regarding their energy use involves both their social networks and the local urban morphology formed by the networked buildings. Although the theoretical foundation exists, very little attention has been simultaneously given to energy use in social and building networks. In fact, a recent report by the National Academies specified that in order to advance our fundamental understanding of network dynamics we need to empirically study network structure, function and dynamics in conjunction with computational modeling efforts [87]. The energy conservation context under which we examine the potential for a network synergy effect is an ideal class of network problem to examine synergies that may exist at the intersection between human and engineered networks. Departing from existing theoretical foundations which confirmed the inter-building effect and the peer network effect but treated them as independent entities [4, 9, 42], our goal in the research we describe in this paper is to extend our understanding of energy conservation strategies by examining the synergy that may exist between “engineered” building networks and “social” peer networks.

In this study, we will quantitatively explore the energy savings derived from both PNEs and IBEs. We focus specifically on the additional energy saving potential that results from the interactions between the two effects. Discovering the synergies that may exist at the

intersection of the two effects can lead to an integrated model of networked occupants at the inter-building level. Our model will not only fill a theoretical gap in the study of energy and buildings, but will also shed light on network-wide intervention design strategies in practice.

3.4 Research Method

The IBE can be characterized as the impact of the infrastructural layout or building modifications on the energy consumption of nearby buildings [4, 35], while the PNE is the impact of the inter-occupant relationships on building energy consumption. In this paper, we put forward the concept of a network synergy effect (NSE) which refers to the potential energy savings beyond the savings associated with the PNE or the IBE separately. We hypothesize that if both a PNE and an IBE are simultaneously observed, a NSE may occur.

To explore this potential synergy, in Section 3.1 we first develop a test case using computational simulation tools to discover an example of the IBE over which a PNE and NSE might occur. Then, in Section 3.2 we explore the choices made by real homeowners given this test case scenario through analysis of survey responses to determine whether a NSE can be identified.

3.4.1 Inter-Building Effect Test Case Simulation

Test Case Block Description

For the test case, we designed an American neighborhood block of six urban residential single-family houses (Fig. 11) located in Atlanta, GA. The six houses are of three different structural configurations with sizes of 10m x 10m, 7m x 10m, and 14.3m x 10m respectively, and are identified by the numbers shown in Fig. 11. We used Google Maps to capture a real

block configuration in Atlanta and arranged the test case configuration to closely approximate a real block configuration. Every house in the test case has two floors: on the ground floor there is a kitchen, a living room, a connection area, and a bathroom; on the upper floor, there are two or three bedrooms, and a bathroom. The layout of the indoor zones, the infrastructural properties and the materials such as gypsum plastering, concrete block, XPS extruded polystyrene, and brickwork were designed according to common construction practices by analyzing several homes in the southern United States [88], the larger geographical region in which Atlanta is located. Every indoor thermal zone was described by specific occupant schedules [26], which associate appropriate internal gain values to daily activities.

Located at $33^{\circ}45'18''\text{N}$, Atlanta has a subtropical climate with hot summers and mild winters. Furthermore, the UHI phenomenon in Atlanta produces temperatures up to 5°C higher than the surrounding areas [89]. Both facts lead to infrastructural interventions like local shading, e.g. the use of overhangs to mitigate the local thermal environment. The need for these types of infrastructural interventions during the summer was the primary reason we chose Atlanta as the city in which we situated our test case.

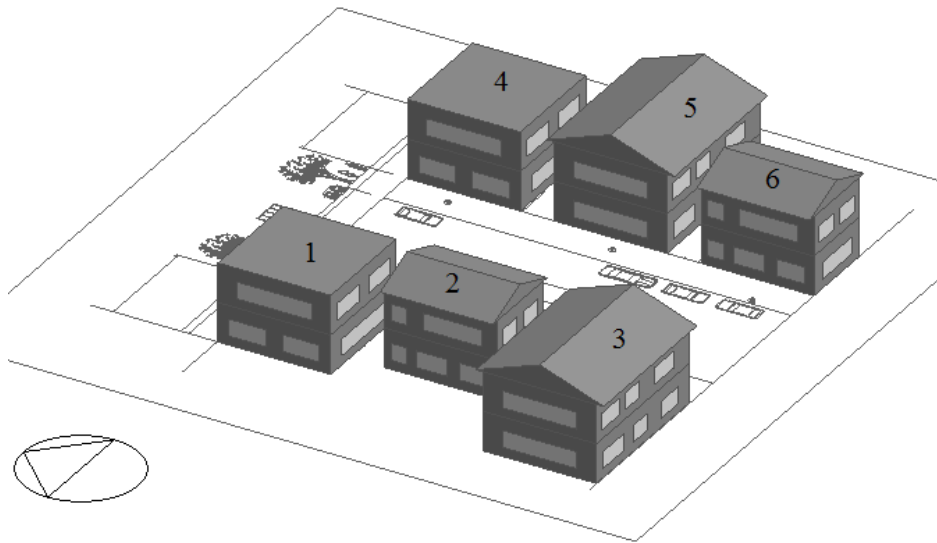


Figure 11. Urban residential block modeled

Inter-Building Effect Modeling

We adopted EnergyPlus (EP) as the building simulation engine combined with the DesignBuilder interface for our study. EP is a whole-building energy simulation program capable of fully integrating the building envelope, HVAC&R (Heating, Ventilating, Air-Conditioning, and Refrigerating), water and renewable energy into the simulation. The newest version of EP can perform advanced fenestration calculations, which enhances its capability to incorporate shading modifications into our energy simulation. For details on EnergyPlus' capability and settings for simulating inter-building effect coming from multiple buildings' interrelationships and environment contexts, refer to [4].

In the first step of the modeling procedure, we simulated the energy consumption of the neighborhood block as a base case using EP. In the second step, widely used and easily installed overhangs were chosen as a local shading infrastructural intervention. Specifically, we installed an overhang with 2.5m projection onto a house's living room window facing the

street. We then simulated the change in energy consumption from the base case and evaluated its IBE. For the third and final step, we installed an overhang to Building3's living room window on either the north side (see grey panel in Fig.12) or the south side (Fig. 13). We then observed the energy consumption impact on Building 3 itself, on the adjacent Building 2, and on the entire block. Based on the monthly average maximum temperature for Atlanta, we chose the warm-season months from May 1st to September 30th as the simulation period.

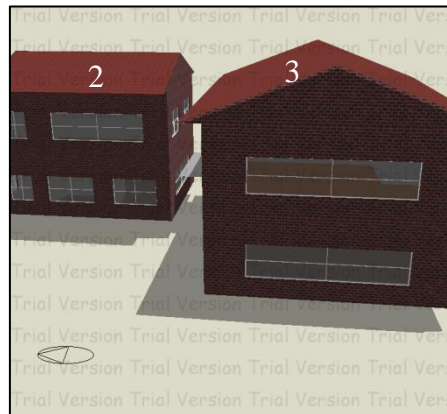


Figure 12. Overhang on the north side

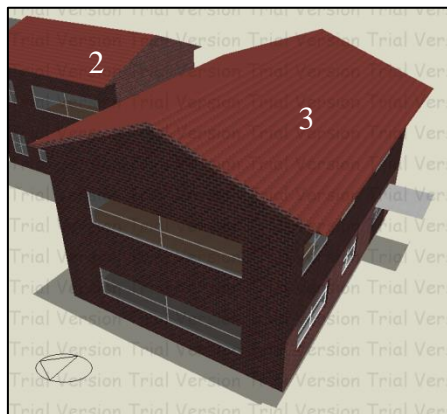


Figure 13. Overhang on the south side

Confirmation of an Inter-Building Effect

Table 6 displays the energy consumption of the cooling system across the whole simulation period for one house at a time and for the block as a whole for simulation scenarios either with or without an overhang. The unchanged energy use in hot water, lighting and other room electricity usage given the same thermal zones' schedules indicates that the variation in total energy consumption is identical to the variation in cooling energy consumption.

Table 6. Inter-building effect of overhang installation

HVAC (kWh)	Blg 1	Blg 2	Blg 3	Blg 4	Blg 5	Blg 6	sum	block	IBE
without overhang	4352	3356	4955	4352	4955	3356	25326	24032	5.1%
with overhang	4142	3145	4571	4150	4593	3151	23752	22069	7.1%
Savings	4.8%	6.3%	7.7%	4.6%	7.3%	6.1%	6.2%	8.2%	--

Simulating one house at a time, Column 2 (“Bldg 1”) through Column 7 (“Bldg 6”) shows energy use by a single house before and after the installation of the overhang. The “sum” column indicates that the six houses together would consume 6.2% less energy than the base case, regardless of the adjacent buildings. On the contrary, simulating the block as a whole (the “block” column), we observe an 8.2% reduction in energy consumption, which is a 2% difference from the result without accounting for the IBE. Moreover, the energy conservation achieved through the IBE is greater than the savings observed for any of the individual houses.

To explain these differences, we calculated the IBE as the percentage change between the “block” and “sum” columns both before and after the local shading intervention. We found the IBE of the base case to be 5.1%, i.e. the block as a whole consumed 5.1% less energy than the summation of each house’s individual energy use. This result occurs because the mutual

shading of adjacent buildings helps the other buildings to reduce cooling energy use in the summer. As a comparison, we found that the overhang installation had an IBE of 7.1%, which is larger than the initial 5.1% IBE. Thus, the IBE of the local shading intervention is not totally attributable to the mutual shading of the adjacent buildings. This is because the overhangs shade not only the building on which they are installed, but also shade the common space shared by the neighboring building, which enlarges the overall shading zone.

The block configuration described in this section that will be used as our test case exhibits an IBE. Thus, we have confirmed previous research [4, 35] that demonstrates that the infrastructural layout and building modifications can impact the energy consumption of the whole building network.

Energy Simulation Test Case

Installing an overhang on the north or south side living room window of Building 3 influenced Building 2. The extent of the influence due to the north or south side overhangs are represented in Fig. 14. We observed that the solar gains through the exterior window of Building 2 were reduced by 8.0% in a typical summer month (August) when the Building 3's overhang is installed on the north side compared to the south side, which will lead to Building 2's energy reduction in the summer. In other words, an IBE exists for a single panel of overhang, thus infrastructural modification in Building 3 could impact Building 2's energy use.

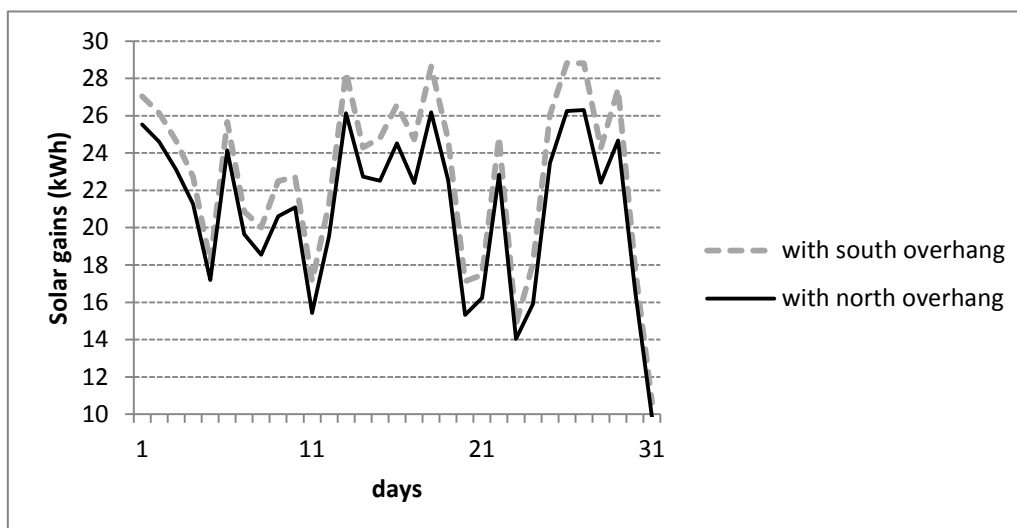


Figure 14. Solar gains through exterior windows of Building 2's living room in August

In contrast, the overhang on the south side of Building 3 will benefit Building 3 more in the summer, since sunlight originates from south for most of the day. In Figure 15, we show how the overhangs impact energy conservation for Building 3 and for the block as a whole.

The data presented in Fig. 15 demonstrates an interesting relationship between the energy saved by an individual building and the energy saved by adjacent buildings. For the individual structure (Building 3), the south overhang reduces energy use by 123kWh over the study period, saving 11.8% more energy than the north overhang's 110kWh reduction. Thus, the south overhang is the preferable option in order to reduce the energy consumption of Building 3. However, in terms of the energy reduction for the entire neighborhood block, the north overhang on Building 3 can save 21kWh energy for other buildings, leading to a total savings of 131kWh when the savings for Building 3 is added to the savings of the block. The south overhang only produces 2kWh in energy savings for the other buildings, which leads to only 125kWh in energy savings for the block. Thus, the north overhang is capable of saving more energy for the entire neighborhood block when the buildings exhibit an IBE.

The 21kWh externality of the north overhang mainly results from its direct shading on Building 2's living room (Fig. 14). The minor 2kWh external energy savings due to the south overhang may be derived from the smaller IBE related to the block configuration. In other words, if it did not cast direct shading, the overhang would have negligible impact on nearby buildings.

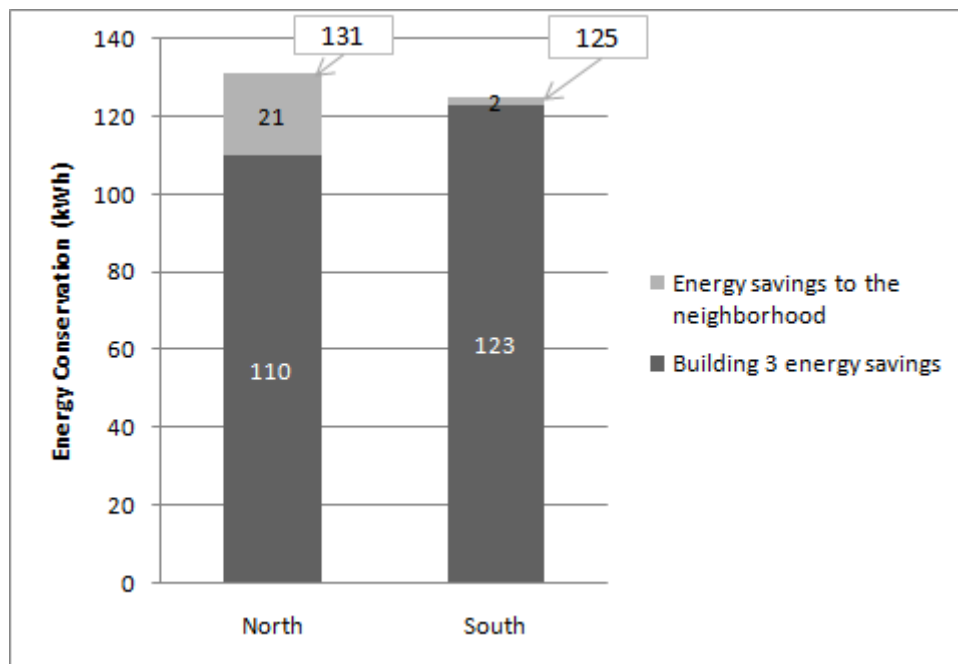


Figure 15. Synergy of inter-building effect and peer network effect

3.4.2 Investigating the Existence of a Network Synergy Effect

The simulation has demonstrated that some interventions may produce higher savings for an individual building while other interventions may produce lower savings for an individual building but higher savings for the neighborhood in aggregate. Given that many homeowners have social relationships with their neighbors, it is possible that their choice of intervention (i.e. whether to maximize the own energy savings or maximize the energy saving of their neighborhood), will be based on the strength of these relationships, which drives toward the

network-wide optimal outcome. In order to examine whether homeowners would, in fact, make decisions about interventions with IBEs based on their social relationships with their neighbors, we designed a neighborhood energy retrofit survey that presented homeowners with the test case described above.

Introduction of the Survey

The survey included four multiple choice questions in a set of home retrofit scenarios, and was designed to take approximately 10 minutes to complete. Participants were homeowners older than 18 years of age recruited by the Community Alliance for Energy Efficiency (CAFE²). After receiving approval from the Institutional Review Board (IRB) at Virginia Tech, links to access the online questionnaire were distributed to the provided CAFE² community email list of homeowners. Information regarding the study was provided in the email as well as on the first page of the questionnaire when the participant followed the link. Participation in the survey was voluntary and a participant could opt out at any time during the survey.

The answers to the questionnaire were automatically collected and recorded by the Survey Monkey website. The online survey was open from February 16, 2012 to March 1, 2012. Among the 109 homeowners who were sent the survey link, the total number of homeowners who started survey was 36 and the total that completed the survey was 35 by the end of the two-week study period. The survey response rate was 32% which was sufficient to examine our posed hypotheses regarding overall retrofit decisions in this pilot study.

Network Synergy Effect Survey Hypotheses

In the survey, each homeowner was asked to choose between an overhang on the south wall (maximal individual benefit) and an overhang on the north wall (maximal neighborhood benefit) given various types of information about the test case scenario and hypothetical social relationships with their neighbors. Given that the two options only differ in position, cost of the overhang is not a consideration in their decision-making process. Each of the four questions included in the survey correspond to four hypotheses about the relationship between homeowner choices and information regarding the test case scenario. Hypothesis 1 is intuitively based on a self-benefit maximizing approach to decision-making, and serves as the baseline scenario from which we will make statistical arguments regarding Hypotheses 2-4.

Hypothesis 1. Homeowners will select a self-benefit maximizing retrofit (south side) when information about *neither* their hypothetical social network *nor* the IBE of the intervention on energy savings is given.

Recent research has verified that the close spatial relationships of buildings and urban morphology within a local network of buildings could produce considerable changes in network-wide indoor operative temperature dynamics[4, 35], which is a cornerstone for realizing NSE. But with the mere knowledge of this IBE, residents may not have sufficient incentive to choose a retrofit that benefits their neighbors and leads to optimal aggregate energy consumption. This motivates the Hypothesis 2.

Hypothesis 2. Homeowners will select a self-benefit maximizing retrofit (south side) when

only information about the IBE of the intervention on energy savings is given.

On the other hand, if an individual's decisions are conditioned by their social relationships, then a PNE exists. To investigate the choices made by homeowners when only presented with information about the hypothetical social relationships with their neighbors, homeowners were asked to imagine that their neighbors were trying to persuade them to install the overhang on the north wall. However, the neighbors did not give any reason why the homeowner should install the overhang on the north (i.e., the IBE is not known). For each level of relationship between the homeowner and their neighbor (i.e. stranger, acquaintance, friend, close friend), the homeowner was asked to indicate whether he or she would choose to install the overhang on the north wall (in accordance with their neighbor's suggestion) or on the south wall (the self-benefit maximizing option). In this way, the homeowner was hypothetically placed in a social relationship context, but was not given any information regarding the IBE of the two retrofit choices. Without IBE, PNE would have no grounds upon which to influence the neighbor's decision. Thus we expect homeowners to make the same decision as H1 when they find the neighbors' persuasion unreasonable. We still also want to isolate the pure PNE's impact in Hypothesis 3, so as to compare the magnitude of the PNE when examining the NSE later.

Hypothesis 3. Homeowners will select a self-benefit maximizing retrofit (south side) when only information about the hypothetical social relationships with their neighbors (e.g. whether they have a close relationship with their neighbor) is given.

As Guagnano's theory implies [85], if the integration of both contextual factors provides favorable incentives for energy conservation in some situations, the behaviors of the occupants can be shifted towards making decisions that conserve energy. In cases where choices about interventions with an IBE exhibit a PNE, we would have evidence that a network synergy effect (NSE) exists. In other words, if the owner of Building 3 chooses the north overhang because they want to increase the energy savings of their close friend (who owns Building 2), the interaction between the IBE and PNE would lead to an NSE by achieving the aggregate optimal result.

Hypothesis 4. Homeowners will select the retrofit that benefits the neighborhood (north side) when information about the IBE and their hypothetical social relationships with their neighbors (e.g. whether they have a close relationship with their neighbor) are given.

3.5 Network Synergy Effect Results

For Hypothesis 1, where neither social network nor IBE information was given, 100% of the homeowners chose the self-benefiting retrofit option, i.e. to install the overhang on the south wall, confirming H1.

For Hypothesis 2, homeowners were provided with the energy conservation benefits of the renovation for each house with no indication of the social relationships that may exist across homeowners. In this case, 69% of homeowners chose to install the south overhang, which maximized benefits for themselves (Fig. 16). Given information on the IBE, the adoption rate of the south overhang decreased from 100% to 69%; however, still most homeowners chose the self-benefit maximizing option without knowledge of inter-occupant

social relations.

For H3, no homeowners followed the suggestion of their neighbor if they were strangers or acquaintances (Fig. 17). However, 11% of homeowners chose to install the north side overhang if they were friends with their neighbor and 19% chose to install the north side overhang if they were close friends with the neighbor. We applied a paired samples t-test between the H1 and H3 responses which resulted in a p value of 0.1022; in other words, the adoption rate of the north overhang from H1 and H3 are not statistically distinct. Thus the statistical result supports rejecting the null hypothesis for H3. In other words, there is no statistically significant support to argue that homeowners will select a neighborhood-benefitting retrofit if only the PNE information is provided.

For H4, IBE information and social network information was provided to the homeowners. When the social relationships of the neighbors were coupled with information about the IBE, 31% chose the option that benefits their neighbor when their neighbor is a stranger, 39% when their neighbor is an acquaintance, 58% when their neighbor is a friend and 69% when their neighbor is a close friend. We applied a paired samples t-test between H1 and H4 and found a p value of 0.0058, which provides strong evidence to reject the null hypothesis of H4 and thus provides support for H4. Alternatively, we can regress the four percentages in H4 over the corresponding four levels of interpersonal closeness, the obtained p values for the slope and the constant are 0.011 and 0.055, respectively. Considering the 0% in H1, the p values mean that the north overhang adoption rates in H4 are not only distinct from those in the base case but also the distinction enlarges as closeness level increases.

We conclude that either knowledge of IBE or close interpersonal relationships between

residents can slightly shift decision making toward the retrofit option that benefits the neighborhood with the IBE information being more effective at influencing choice compared to a homeowner's social relationship. However, when examined separately neither the IBE nor the PNE significantly influences homeowner's energy efficient retrofit decision-making. Yet, when both types of information are available to homeowners, much higher adoption rates for the retrofit option that benefits the neighborhood are observed compared to when the homeowners have only IBE information or only social relationship information. We found that only when both effects were engaged did a statistically significant change in decision-making occur. In sum, we found that limited savings occurred when either PNE or IBE were known, but a significant network synergy effect resulted in much greater potential energy savings when both the PNE and IBE were known to decision-makers.

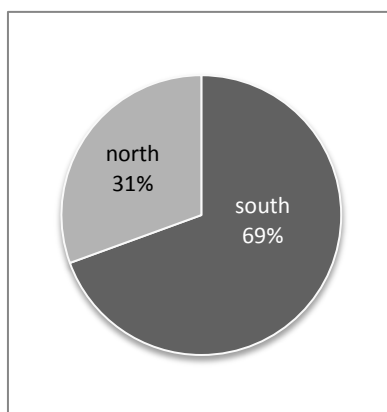


Figure 16. Overhang choice under H2

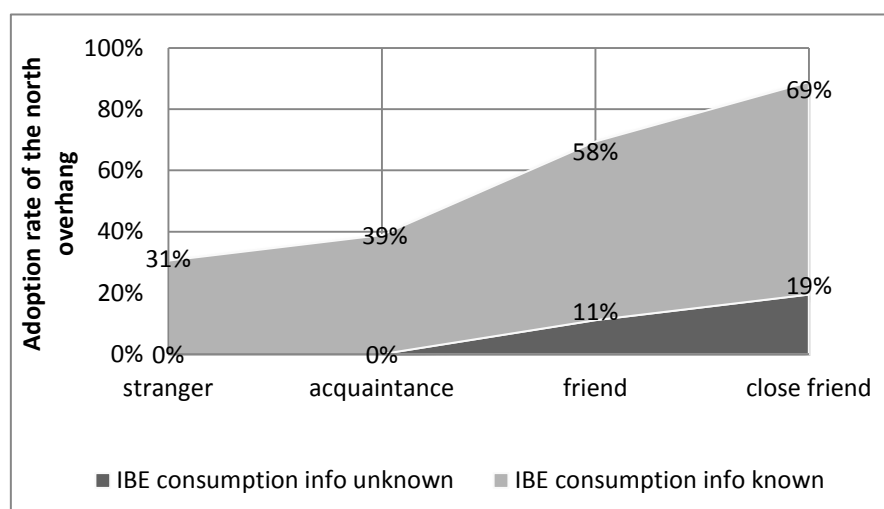


Figure 17. Overhang choice under H3 and H4

3.6 Discussion

Theoretical research has emphasized the importance of context in driving pro-environmental behavior [43]. The inter-building effect [2] and peer network effect [6] have been shown to exist as contextual factors of energy conservation [9]. However, we lack studies that examine the influential power of the interaction between building networks and occupant networks at the intersection between the IBE and the PNE. Our research confirms that a synergy can exist between these two effects. This is crucial to our understating of building energy saving potential because the network synergy effect may be a more effective context in which greater aggregate energy savings can be achieved compared to either effect in isolation. Consequently, we found with statistical significance that the aggregate energy savings for a neighborhood block when both effects are present is higher than the sum of the individual effects.

Beyond demonstrating the existence of the NSE, our research also provided some insight into the nuanced difference of the magnitude of all three effects for our test case. We observed that providing homeowners with IBE information in the context of a PNE can result in the

highest rate of choice for the modification that benefitted the whole block at the expense of maximizing their own energy savings. In Fig.17, the 31% adoption rate when only IBE information is given plus the 19% adoption rate when only strong personal ties (i.e. close friends) are substantially less than 69% when both conditions are present simultaneously. Recall that the energy saving of the block is proportional to the north overhang adoption rate in our test case. Hence the magnitude of NSE is greater than the sum of the magnitude of IBE and PNE.

As an external validation of this finding, the critical role of the factors' interaction in order to achieve an amplified aggregate effect was similarly identified, but it was based on multiple energy retrofit measures [76]. There is another way to demonstrate that the combined knowledge of the impact of retrofits on neighboring buildings and strong personal relationships between inhabitants across buildings can drive retrofit decision-making toward optimal energy consumption outcomes. It is notable that the 31% north overhang adoption rate in Fig.16 when social network information is not present is identical to the 31% adoption rate in Fig.17 when residents do not know each other, which justifies the consistency in responses and represents the pure IBE. It indicates that the upward trend of the lightly shaded area's top line beyond the 31% level in Fig. 17 is because of the PNE and the interaction between the IBE and the PNE, i.e. the total NSE less the pure IBE. Comparing it with the line on top of the lower dark shaded area, which represents the pure PNE, we are able to determine the magnitude of the interaction between the IBE and the PNE. As a result, evidenced in either the increasingly wider gap between the two trend lines or the positive difference between their slopes of 0.136 and 0.069 obtained by regressing over the relationship levels on the x-axis denoted as from 0 to 3, we

conclude that the interaction between the IBE and the PNE positively contribute to the energy savings. In other words, the effect of the social network is stronger when the IBE is known compared to when it is unknown.

In order to create a standard assessment capable of determining the existence of a network synergy effect (NSE) for future studies in other contexts, we present an approach as a set of criteria in Fig. 18. When the last inequality in the guideline is satisfied, the additional amount of energy conservation represents the NSE.

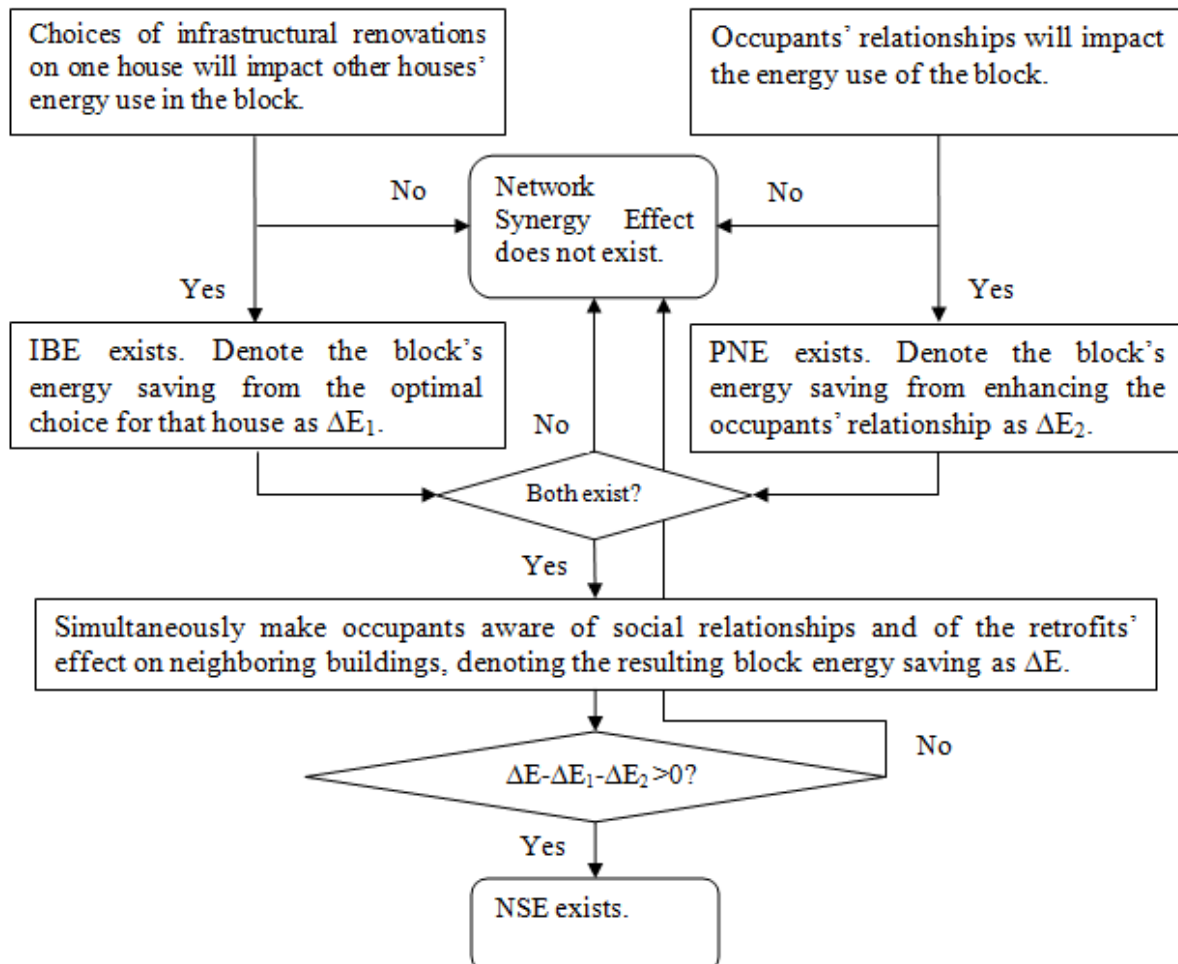


Figure 18. Guideline for assessing the NSE

An occupant network's impact on daily energy conservation relies mainly on the evolution

of habits resulting from peer pressure as shown in current PNE literature. Our research validates this form of positive influence of interpersonal relationships on building energy conservation. However, such influence may dissipate over time, because people move as time elapses, people's relationships may change[90], and relapses in savings due to the PNE have been observed [41]. Unlike these studies, we focus on a point-in-time decision and expect that the resulting saving is likely to be more robust and predictable. Future PNE research may productively examine the influence of an occupant network's role on energy use in the case of other one-time infrastructural modifications.

Last but not least, we have answered a call for fundamental research at the intersection between human and engineered networks. As an ideal class of network problem, the discovery of network synergy effect justifies adopting a network perspective of urban residential buildings and of individuals that occupy them and can further generate interdisciplinary knowledge beyond these findings. Pursuing these research ideas may contribute to greater building energy saving potential. Our findings suggest that energy retrofit projects that leverage peer network relationships along with information about the interactions between thermal performance of buildings may lead to renovation plans that achieve greater aggregate reductions in energy consumption. This paves the way for future researchers to examine IBE, PNE, and NSE as network phenomenon with the aim of energy reduction. For instance, we assume a broad range of infrastructural modifications other than shading devices can produce an IBE, e.g. guiding of air-conditioning plant's exhaustive heat, and the color and reflectance choice of the building envelope. We suggest scholars use the framework we proposed to discover and quantify the network synergy effect as $\Delta E - \Delta E_1 - \Delta E_2$ in other situations. We also

recommend that future researchers employ further empirical studies that explore owner decision-making because these types of studies allow us to develop an understanding of how the NSE can be applied to reduce energy use in a range of authentic contexts.

3.7 Limitations

Our survey results may be biased by the specific community we studied and the relatively small sample size. Yet instead of trying to make a generalizable argument, our objective was to discover as a pilot study whether a network synergy effect can exist which we were able to confirm with this population of survey respondents. For future studies, economic inputs that may affect a homeowner's decision to adopt energy-saving renovations may also be added [79] to add additional realism to the scenarios posed to the survey respondents. Our choice of urban area, the block layout, the number of buildings, the infrastructural properties, the retrofits, etc, all focuses our results to a very specific context. We identified the existence of a network synergy effect in a particular scenario, yet at this point, we cannot generalize our findings to other contexts. In order to fully realize the applicability of the network synergy effect in encouraging large-scale energy reduction, the network synergy effect should be examined in a variety of contexts, considering a variety of retrofit options.

3.8 Conclusion

In this paper, we discovered that a network synergy effect can exist at the intersection of building networks and residents' social networks. We demonstrated that it can lead to greater aggregate neighborhood-wide energy efficiency. In the first part of the study, we built a model in EnergyPlus of a six-house residential block and adopted a local shading device as an infrastructural modification. After simulating the block energy use for several scenarios, we

found that the renovation impacted the energy consumption of nearby buildings, which indicated the existence of an inter-building effect. Most importantly, we observed that a modification that was less energy efficient for a single house was more efficient for the whole neighborhood block when the inter-building effect was included in our test case scenario. We hypothesized that the peer network effect, i.e. the impact of the inter-occupant relationships on building energy consumption, may result in the optimal, aggregate energy savings outcome when coupled with knowledge of the IBE.

To test our hypothesis, we conducted a neighborhood energy retrofit survey with the purpose of examining real homeowners' choices. Our results show that 69% of the homeowners selected a retrofit option that saved more energy for their neighbors but less energy for themselves when: (i) they were aware of the inter-building effect, and (ii) they were close friends with their neighbors, which implies a peer-network effect on their choice. The aggregate energy savings for the neighborhood block when both effects are present is discovered to be higher than when either effect is present and even when their individual effects are summed. For the first time, we define this type of additional energy saving potential as the *network synergy effect*. Having demonstrated the existence of the network synergy effect in a particular scenario, we presented guideline criteria based on the definition we posited in order to aid future researchers in identifying the network synergy effect in other contexts.

Chapter 4

4. ENERGY SAVING ALIGNMENT STRATEGY: ACHIEVING ENERGY EFFICIENCY IN URBAN BUILDINGS BY MATCHING OCCUPANT TEMPERATURE PREFERENCES WITH A BUILDING'S INDOOR THERMAL ENVIRONMENT

4.1 Abstract

Existing strategies for residential energy savings through physical renovation or motivating occupant energy conservation behavior can be costly and/or have transitory effects. Focusing on multi-family dwellings, an important subset of the urban residential sector, we propose an Energy Saving Alignment Strategy (ESAS) that has advantageous cost-effectiveness and a long-lasting influence. By aligning the distribution of residents' thermostat preferences with the indoor temperature, ESAS aims to maximize thermal comfort and, accordingly, energy savings in multi-family buildings where indoor temperatures vary between apartments as a function of apartment orientation and floor level. Using a case study of a 1084-apartment public housing complex in New York, we classify both occupants' thermostat preferences and apartments' operative temperatures into five groups, and optimize energy efficiency by assigning each group of occupants to the group of apartments that best aligns with their thermostat preference. We test ESAS in eight cities representing all four U.S. census regions and six climate zones. Simulation results reveal 2.7% to 34.7% in energy savings compared to random apartment assignments depending on geographic location, with the highest energy reductions occurring in cities with mild climates, where the range of occupant thermostat

preferences coincides with the natural indoor temperature range. We conclude by providing suggested guidelines on how ESAS might work in practice, and recommendations for extending ESAS research.

4.2 Introduction

Responsible for 22% of the primary energy consumption and 17% of the total greenhouse gas emissions in the U.S., the residential sector is a centerpiece of the policy debate on energy efficiency [91]. Energy for heating and cooling homes comprises approximately 43% of this residential energy use, or 9.5% of the total U.S. energy consumption [92]. Since expected reductions in household energy use due to increased efficiency of appliances will be more than offset by increases in population and appliance usage, residential energy consumption is projected to continue increasing from now to 2040 unless there are significant changes to the nation's energy policy [93]. Going forward, the reduction of residential energy consumption, especially that attributable to space heating and cooling, constitutes a key challenge in the larger push towards a sustainable built environment.

An important area for energy use improvements is in dense urban residential environments, including public housing [8]. More than 5 million American families—living in approximately 5% of all housing in the nation—receive housing assistance from the Department of Housing and Urban Development (HUD), which also oversees all federally assisted public housing, owned directly by its 3300 Public Housing Authorities (PHAs), for 1.3 million American families. The high energy usage and resulting utility costs associated with such subsidized housing units have added great financial burdens to the government and tenants [94]. In any single year, HUD's annual energy bill for its housing programs is around \$4 billion—more than

10% of its budget—primarily through utility allowances to renters that cover their reasonable utility costs and operating grants to PHAs [95].

In addition to being a sizable proportion of the residential sector, public housing is less energy efficient than conventional private housing on a unit-area basis, indicating great potential for energy savings [96]. However, despite well-intended energy saving efforts, HUD reported shaving off only \$33 million of its 4-billion dollar energy bill in its FY2009 report to Congress, which is less than 1% in actual monetary savings. Whether the housing authority pays for some or all of their energy usage, residents might still be disadvantaged by high utility costs, because resources expended on such costs could be more productively spent on necessary infrastructure improvements [97]. HUD believes that properly designed initiatives for future energy efficiency could yield significant cost savings to the federal government, to property owners, and to the building residents themselves [95].

The traditional methods adopted for reducing energy use for space heating and cooling involve physical modifications to existing building exteriors and/or interiors [3]. In 1982, the San Francisco Housing Authority began installing attic insulation and water-heater blankets in its buildings to reduce rapidly increasing energy expenses [98]. A more recent class of saving methods is related to control and optimization techniques targeted at occupant behaviors and the motivation of energy conservation measures [3, 9]. As buildings become more energy efficient, the behavior of occupants plays an increasingly important role in energy consumption [7]. Indeed, behavioral factors, such as the thermostat settings and the use of personal heating/cooling devices, have been shown to explain about 30% of the variance in overall heating consumption and 50% in cooling consumption [8].

However there exist certain limitations to energy savings strategies that involve physical interventions and/ or behavioral modification strategies. Specifically, interventions to improve the energy performance of the physical building and the advanced systems required to monitor occupant behaviors can be costly and time-consuming to implement and maintain. While some behavioral strategies can achieve energy savings without the expense of added infrastructure, their effect is generally transient unless homeowners are motivated periodically to revisit their energy consumption patterns [6]. In this study, we try to overcome the limitations of existing energy efficiency approaches and advance the current trend of capitalizing on occupant behaviors to reduce building energy demands by proposing an innovative Energy Saving Alignment Strategy (ESAS) that has advantageous cost-effectiveness and a long-lasting influence, a combination which is oftentimes missing in current energy strategies. We chose to explore the application of ESAS in the context of public housing, due to the need identified above for energy efficiency in this sector. Nonetheless, the principles behind ESAS are applicable to private and institutional multi-family housing and could provide a promising solution to reducing the current, energy footprint of urban residential building stock.

4.3 The Influence of Thermal Comfort on Energy Consumption

Thermostat management has been widely introduced into residential buildings with two major goals: (1) energy saving and (2) improvement of occupant thermal comfort [99]. Vine [100] recognized many years ago the ease and effectiveness of thermostat management, e.g. that decreasing and increasing thermostat set-point temperatures during winter and summer, respectively, is a means to reduce energy consumption in buildings, and he proposed that this temperature management strategy should be considered prior to more time-consuming and

expensive energy-reducing measures such as ceiling and wall insulation. Nevertheless, this type of behavior motivation may be merely transitory because people may start to keep their homes warmer in the winter and cooler in the summer if they believe the campaign has ended; usually the decision is left to the occupant if (and how much) it is worthwhile to adjust the thermostat set-point temperature at the expense of thermal comfort. A more sophisticated approach is one in which occupants set different night- and day-time setback temperatures to account for periods with no active occupancy, which saves heating and cooling energy without diminishing thermal comfort. Ben-Nakhi and Mahmoud [101] used neural networks to optimize the end time of the thermostat setback such that the thermal comfort and energy demand of the subsequent hour would not be impacted by the temperatures during the setback period. Most recently, Al-Sanea et al. [40] produced an optimized monthly-fixed thermostat, accompanied by proper thermal insulation, where indoor air temperatures are selected within the summer and winter comfort-zones in a manner that provides the highest occupant comfort-level while maximizing energy savings. This latter study marks a notable trend in thermostat management: namely, organizing building operations around the proper combination of thermal comfort and energy savings, as opposed to viewing these selections as a tradeoff. The success of the combination roots from the fact that energy for space conditioning is most likely to be minimized when residents' thermal comforts are satisfied.

The above efforts capitalize on the dynamics of thermostat settings to achieve combined energy saving and thermal comfort. However, an alternative approach is to match the natural indoor temperature of a housing unit to the thermal comfort preferences of a unit's inhabitants, given the distribution of thermostat settings. That a range of comfort preferences exist between

households is attributable to wide variations in occupant habits, lifestyles, and perceptions of comfort [7]. In fact, such individual factors, e.g. a preference for air conditioning while sleeping or working, have an impact on the energy for space conditioning used in winter that is eight times higher than that of environmental factors [39]. In Langevin et al. [8] semi-structured interviews to explore the key behavioral tendencies among low-income public housing residents found significant differences among resident's indoor thermal preferences. Specifically, 35% of those interviewed reported satisfaction with indoor temperatures, while one third reported "sometimes satisfactory" and the last third reported "frequent problems" with the indoor climate. These findings are reinforced by Peeters et al. [102], who point out that it is impossible to satisfy the comfort preferences of all persons in a large group sharing a collective climate. That there is an opportunity to leverage the differing thermal preferences of building residents arises from the fact that the range of preferred thermostat settings between households can be significant, with some reported settings falling below 68°F (20°C) in the winter and others above 78°F (25.6°C) in the summer: where 20°C and 25.6°C are the assumed preferred household winter and summer temperatures, respectively, used in many energy programs [100].

The above findings on varying thermal preferences and perceptions of comfort among building occupants, together with the notion of combined thermal comfort and energy savings, have led us to design a novel Energy Saving Alignment Strategy (ESAS) for multi-family residential buildings that seeks to match the indoor thermal preferences of a household to the thermal conditions within an apartment. By placing each household in a housing unit that has a natural temperature closest to their preference, we expect to obtain the highest thermal comfort

satisfaction, and consequently the lowest space conditioning demand and resultant energy use. Despite interesting and relevant questions raised in Vine's study [100] to inspire such alignments, studies that explore the possible impact on energy consumption of this concept are currently lacking. Here, we present an exploration into the design and implementation of ESAS in different US climate zones using New York City Housing Authority (NYCHA) public housing typology as a base case study. In what follows we describe the data collection of the case study, the derivation of the thermostat preference distribution and the indoor temperature distribution, and the alignment methodology in Section 3. The simulation results are presented in Section 4 and generalized to various climate contexts in Section 5 where guidelines for implementation are also given. Conclusions and future research directions are provided in Section 6.

4.4 Data and Method

4.4.1 Case Study Description

The case study is Amsterdam Houses, a public housing development operated by New York City Housing Authority (NYCHA). Completed in December 17, 1948, Amsterdam Houses consists of 13 residential buildings on a 9.49 acre lot, ten of which are 6 stories high while three are 13 stories high. Its 1,084 apartment units house an estimated 2,329 people. Figure 19 shows the site layout, which was modified from an NYCHA development map, where building and entrance numbers are also shown [103]. Following the Housing Act of 1937 mandating limitations in initial cost and building coverage of government-assisted, low-rental housing, Amsterdam Houses typified the public housing site approach, which became one of the standards for the era: the linear barracks [104]. Occupying two and a half

blocks, the site creates one large “superblock” where city streets are removed.

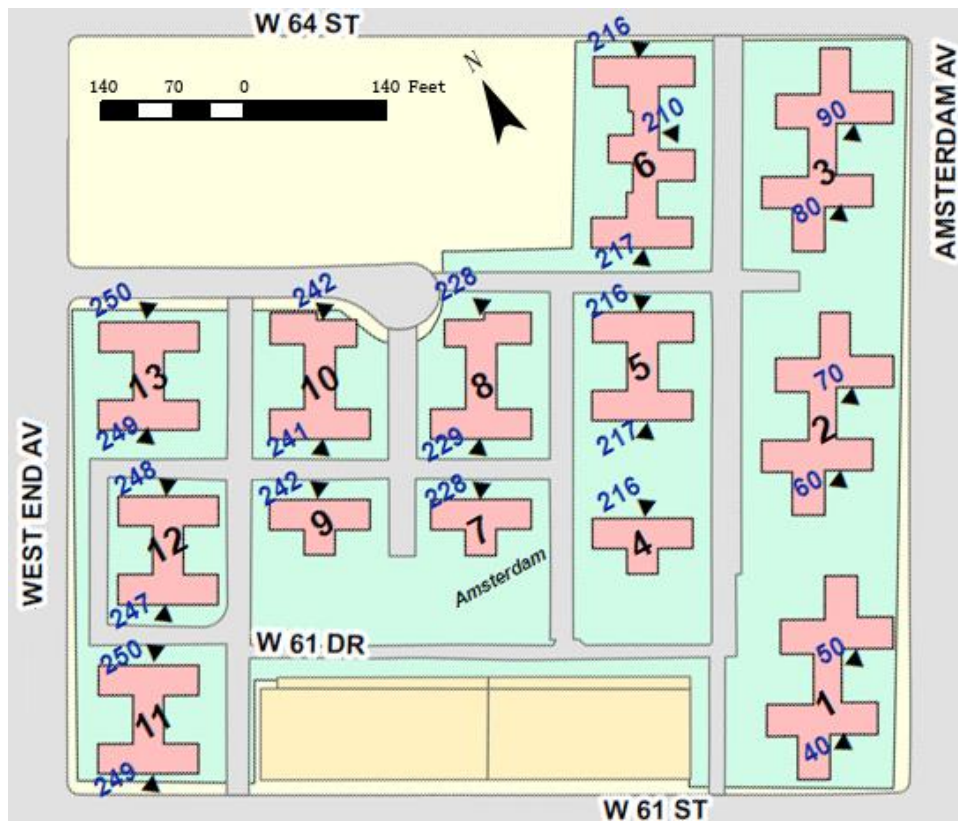


Figure 19. Amsterdam Houses superblock layout

4.4.2 Material Collection and Modeling

We collected the original microfilms of Amsterdam Houses development from the Department of Buildings, which contain information on space types, structure details, equipment systems, and the blueprints of buildings on the lot. Figure 20 displays the floor plan of building 1 located at the southeast corner of the development, which has 14 apartments on each floor. This figure was produced by scanning the microfilm and cleaning extraneous marks resulting from long-time storage. On average, for the whole development, each unit houses approximately 2.15 persons.



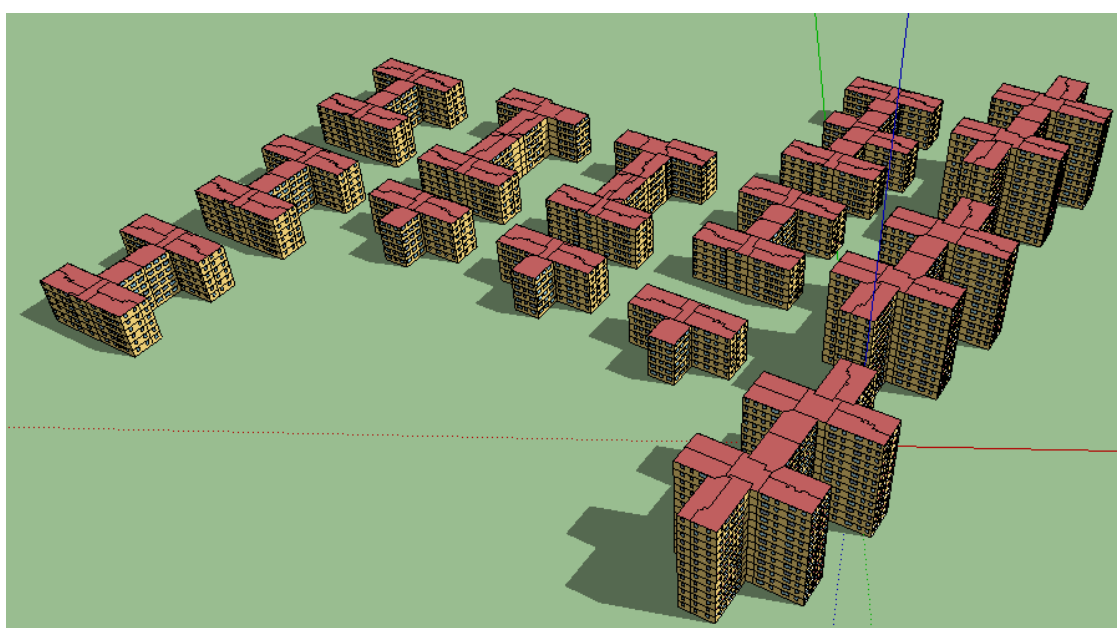
Figure 20. Building 1 floor plan

Several of the cost-saving techniques that dominated NYCHA postwar construction were applied in this project. These included the use of a column and slab concrete structure with cavity wall construction [104]. The specific construction details of external walls, which also served as the NYCHA standard, were obtained from an engineer's report for the Amsterdam Houses [105]. Roof and ground floor construction details are based on the Department of Building's requirement on buildings in the Northeast region with a pre-1980 vintage. Table 7 lists the major architectural elements.

Table 7. Major architectural elements description

Architectural elements	Layer materials and thickness (from outside, in cm)	Thermal properties
Exterior wall	Brick: 10	Conductivity = 1.185 W/mK
	Hollow clay block: 15	Conductivity = 0.822 W/mK
	Air space: 2	Resistance = 0.15 m ² K/W
	Metal furring: 0.2	Conductivity = 44.96 W/mK
	Gypsum plastering: 1.3	Conductivity = 0.16 W/mK
Roof	Roof membrane: 1	Conductivity = 0.16 W/mK
	Deck insulation: 8.8	Conductivity = 0.049 W/mK
	Roof structure: 20	Conductivity = 0.53 W/mK
Ground Floor	Heavyweight concrete: 10	Conductivity = 0.16 W/mK
	Carpet pad: 1	Resistance = 0.217 m ² K/W

After collecting design and construction information, we created a model for Amsterdam Houses in OpenStudio. OpenStudio is developed by the National Renewable Energy Laboratory as a collection of software tools to support whole building energy modeling using EnergyPlus. The finished model, as displayed in its SketchUp Plug-in, is shown in Figure 21, with the rightward axis pointing east. The floor plan of each building is depicted on the roof, and the shadows shown are of a morning in July.

**Figure 21. Superblock model exhibited in OpenStudio SketchUp Plug-in**

4.4.3 Occupant Thermostat Preference Classification

For the purpose of estimating the thermal preference of occupants, we obtained thermostat setting statistics of from the U.S. Residential Energy Consumption Survey (RECS) [106]. The survey summarizes the number of U.S. households choosing each level of thermostat setting under different occupancy (i.e., home or not home) for both space heating and cooling. Referring to the semantics in the commonly used ASHRAE psychophysical scale of thermal sensation (ranging from -3, indicating cold, to +3, indicating hot, with 0 indicating neutral), we generated occupant thermostat preference distribution from the RECS survey and classified it into five categories: cold, cool, mid, warm and hot. As listed in Table 8, we assigned a single set of thermostats to each category based on unit occupancy and season. The cooling thermostat is set to 32 °C for the group of people who report not using air-conditioning during the summer, while for all other groups, the thermostats are the summarized average settings. The classification is done by quantiles, which ensures that each category contains 20% of the population. Because there is no discernible thermostat difference due to occupancy in the RECS data of the Northeast region during the winter, only one temperature per category is assumed. In order to translate the thermostat table to schedule settings in EnergyPlus, we assume “Daytime Temperature When Someone is Home” applies to 8am-6pm during weekends, “Daytime Temperature When No One is Home” applies to 8am-6pm during weekdays, and “Temperature at Night” applied to 6pm-8am for all days.

Table 8. Thermostat settings for thermal preference groups

Preference /Thermostat	Summer			Winter
	Daytime Temp when someone is home	Daytime Temp when no one is home	Temperature at night	Temperature at all time
cold	20.6	20.6	20.6	17.2
cool	21.1	21.8	21.1	18.4
mid	22.3	23.9	23.1	20.4
warm	24.5	26.9	25.6	22.2
hot	32.0	32.0	32.0	23.3

4.4.4 Superblock Simulation and Free-running Classification

In this step, we aim to classify all 1084 apartments in the superblock into five categories by their natural temperature levels. To achieve this, we adopted EnergyPlus to simulate the superblock model in the free-running mode and report the operative temperature, a widely adopted indicator of indoor warmth. A free-running building's indoor temperature, humidity, and other thermal conditions are freely determined by external environments and total heat gains, without the use of mechanical heating or cooling. For the simulation, each apartment was set as a thermal zone, the unit EnergyPlus uses for heat balance calculation. The simulated zone operative temperature (Figure 22) then represents the unregulated thermal environment an apartment provides to its occupants, based on which the occupants will decide if (and how much) space conditioning is needed after room assignment.

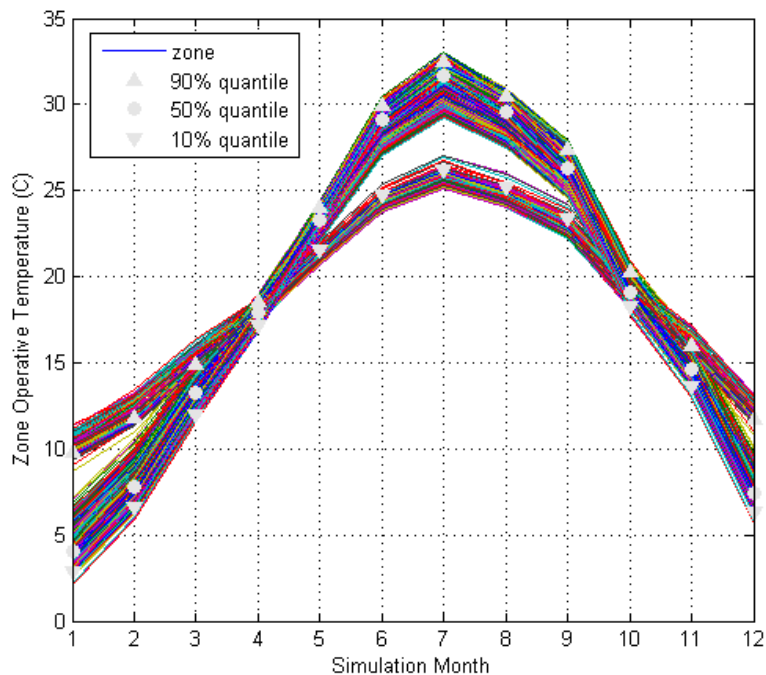


Figure 22. Apartment temperature variation under free-running mode

In Figure 22, the monthly averaged operative temperature for each of the 1084 apartments is shown by one line. Superimposed on top of the 1084 lines are three series of shapes, representing the 10%, 50%, and 90% quantiles of the 1084 values at each month, respectively, enabling the bulk of the temperature range to be visualized over the dense pattern of overlapping lines. Two key observations can be drawn from Figure 22. First, the variation in apartment temperatures across the superblock is wide, especially for the winter and summer months, during which unit-to-unit differences can reach 9°C. This variation means that there is an opportunity within the apartment complex to provide units with different temperature regimes to residents with different thermal preferences. Second, lines cross each other at transitional months like April and October, meaning that some units are warmer than average in winter while cooler than average in summer. This phenomenon is especially remarkable during the coldest and hottest seasons when gaps are visible between the two clusters of lines in

Figure 22. We found that the sub-set of units warmer in the winter and cooler in the summer correspond to apartments on the first (i.e., ground) floor. This occurs because such apartments have direct contact with the earth, which is relatively warmer than the air temperature in the winter and cooler in the summer due to its high heat capacity and the corresponding delay of heat transfer underground. Also, due to the poor insulation of older public housing developments, apartments located on the first floor are influenced by the ground temperature, leading to the observable gap in indoor climate conditions relative to other apartments.

Consistent with the occupant thermostat preference classification categories, we rank the 1084 apartments from cold to hot based on average annual temperature, and again adopt the quantile classification system to ensure each category contains 20% of the apartments. In view of the partly reversed temperature sequence in winter and summer shown in Figure 22, we also classify apartments from cold to hot by their average temperature during summertime and wintertime respectively. Thus, we arrive at three different classifications of the 1084 apartments based on three averaging bases, i.e. whole year, summer, and winter. All three classifications will be tested for alignment with residents' thermostat preferences in the next step, in order to determine the best alignment strategy.

4.4.5 Alignment of thermostat preference and room temperature

The alignment proceeds with assigning families to apartments that provide thermal conditions corresponding to their preference, i.e. assigning families with a cold thermostat preference to apartments marked as cold based on the results of the free-running mode simulations, etc. The alignment is realized in EnergyPlus by modifying each apartment's thermostat schedule to its occupant's thermostat preference group as listed in Table 8. The above alignment procedure is

repeated for all three free-running temperature classifications described in Section 3.4. In order to compare our optimized placement with the current situation in the public housing complex, we make ten additional random assignments, i.e. the 1084 families are randomly assigned to the 1084 apartments. Finally we compare the simulated energy consumption under the three aligned cases with the energy consumption under the random scenarios to determine the significance of the savings attributable to the alignment options and the overall best alignment method.

4.5 Results

4.5.1 Baseline Model Validation

The superblock energy model is validated by both total energy consumption and end use breakdown metrics. Because energy bills of this public housing project are confidential, we adopt publicly available sources for the validation. Figure 23 shows the simulated end use of the baseline case, which is the median of the ten random results, in parallel with the average end use of residential multi-family buildings in Manhattan derived using a top-down method in a previously published study [107]. The annual energy use for domestic hot water, space heating, space cooling, and base electric are 3,526 MWh, 11,777 MWh, 1,390 MWh, and 5,125 MWh, respectively, for the baseline simulation, or equivalently, 17%, 53%, 5%, and 25% of total energy consumed per year. This end use distribution is very close to the benchmark end use, and is comparable with the RECS end use summary of the Northeast region, reporting 19%, 53%, 3%, and 25%, respectively, for each function listed above [108]. In terms of total energy intensity, our model's baseline of 328 kWh/m² is within an acceptable 5% deviation from the benchmark's 312k Wh/m².

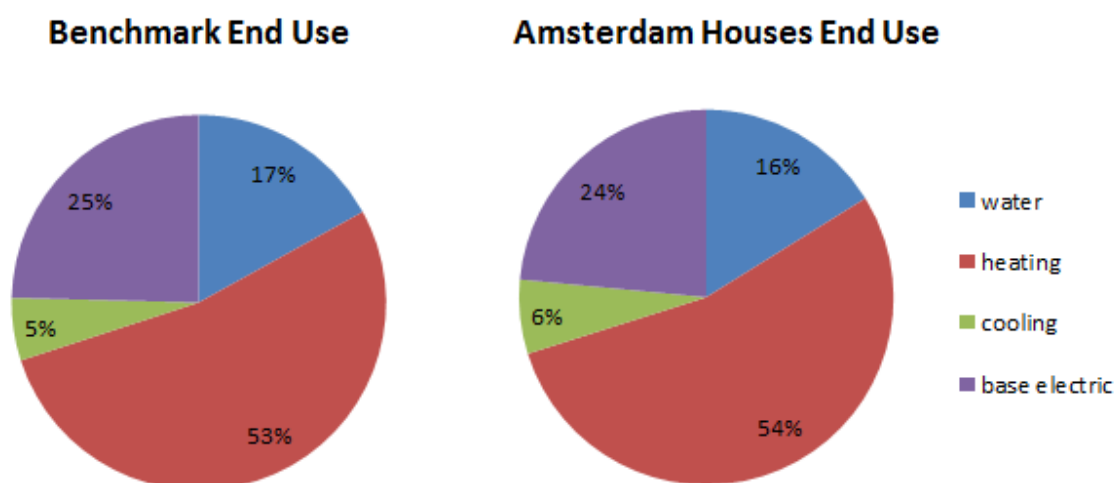


Figure 23. Energy end use validation

4.5.2 Simulation Results Under Random and Aligned Scenarios

Figure 24 displays the superblock primary energy consumption per year under the three apartment temperature classifications against the energy consumption under the ten random assignments. Here the primary energy is comprised of energy requirements for space heating and space cooling. The random assignments have energy consumption ranging from 13,108 MWh to 13,245 MWh. The median of the random results of 13,168 MWh is used as the baseline with which the energy use under our three alignments is compared. The most energy efficient alignment is found to be the one classifying apartments by their summertime temperatures. With 12,676 MWh of energy used, the alignment by apartment average free-running summer temperatures achieves a 3.7% energy saving over a year compared with the baseline. Alignment by winter temperatures, however, results in 13,223 MWh of energy used, which is 0.4% more than the random baseline. As a result of the partly reversed distribution of temperatures during summer and winter, alignment by an apartment's average

free-running temperature over the whole year arrives at an outcome in between, being closer to the summer outcome, with 12,823 MWh of energy used and an associated 2.6% saving over random occupant assignments.

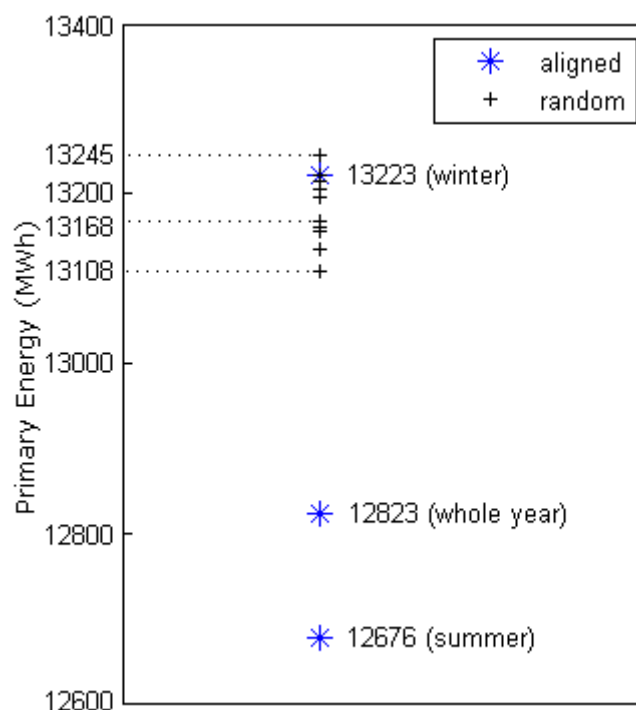


Figure 24. Superblock annual energy consumption under aligned and random apartment assignments

We conclude from Figure 24 that by allocating residents to apartments that have summertime operative temperatures corresponding to their thermostat preferences, the energy savings for the whole Amsterdam Houses project can be 3.7% per year. This energy efficiency outcome is significant, considering that the deviation of random scenarios is merely +/- 0.6% from the baseline, or observing that the alignment results for summer and for the whole year are well away from the range of random outcomes in Figure 24. The practical implications of the alignment strategy are discussed in Section 5.3.

4.6 Results Generalization, Interpretation, and Discussion

In this section, we expand the exploration of the alignment strategy from New York to other representative U.S. cities, which we identified as appropriate for experimentation. Our goal is to evaluate the difference in the energy savings via ESAS based on differing climate conditions. One of our ultimate objectives is to propose priority locations for the potential implementation of the alignment strategy and provide guidelines regarding the underlying conditions for the strategy to be effective.

4.6.1 Cross-region Comparison

We selected two populous cities in each of the four U.S. census regions adopted by the Energy Information Administration to test the strategy's effectiveness in multiple geographic locations.. These cities are regarded as "populous" because they rank within the top 50 cities by population and are located in one of the top 20 metropolitan areas reported by the U.S. Census Bureau [109]. Altogether, they cover zones 1 to 6 of the eight climate zones defined by the widely cited International Energy Conservation Code [110], where zone 7 and zone 8 represent the coldest areas in the U.S. with no populous cities. The eight selected cities were as follows: Northeast Region: New York, NY (zone 4) and Boston, MA (zone 5); Midwest Region: Chicago, IL (zone 5) and Minneapolis, MN (zone 6); South Region: Houston, TX (zone 2) and Miami, FL (zone 1); and West Region: Los Angeles, CA (zone 3) and San Francisco, CA (zone 3).

To facilitate the cross-region comparison, we chose Building 5 (as numbered in Figure 19) instead of the whole superblock for simulation. Again, we evaluated the annual energy savings in terms of the reduced primary energy requirements of the three alignment methods from the

baseline case representing a random unit assignment. At each location, we executed the alignment process again, because the distribution of apartment temperatures varied with the different climates. But for the purpose of controlled comparison, inputs for the baseline case remained the same for all locations except for the weather files.

Table 9. Aligned energy use (MWh) and savings for representative cities in four regions

		Northeast		Midwest		South		West	
		NYC	BOS	CHI	MN	HOU	MIA	LA	SF
Baseline	heating	662	770	855	1082	90	12	89	226
	cooling	79	54	66	59	190	263	68	27
	primary	741	824	922	1141	280	274	158	253
Whole year	heating	644	778	871	1103	70	4	50	170
	cooling	74	52	65	58	183	256	53	16
	primary	718	830	936	1161	253	260	103	186
	saving	3.1%	-0.7%	-1.6%	-1.7%	9.9%	5.1%	34.7%	26.3%
Summer	heating	640	743	831	1058	71	5	56	171
	cooling	71	47	60	52	181	254	51	16
	primary	711	791	890	1110	252	259	107	186
	saving	4.0%	4.0%	3.4%	2.7%	10.0%	5.7%	32.4%	26.2%
Winter	heating	663	787	873	1103	69	4	52	177
	cooling	80	53	65	58	184	258	53	18
	primary	743	840	938	1161	253	262	106	194
	saving	-0.3%	-2.0%	-1.8%	-1.7%	9.8%	4.5%	32.9%	23.0%

The simulation results are listed in Table 9, where the best alignment methods are in bold for each location. The annual energy savings range from 2.7% in Minneapolis to 34.7% in Los Angeles by using the best alignment method. At locations where ESAS achieves the highest energy efficiency, assigning occupants to apartments whose yearly-averaged free-running temperatures correspond to their thermal preference is found to be the best method. Nevertheless, at locations with more moderate savings, alignment on the basis of summertime temperature is most advantageous. Among such locations, those with cooler climate zones, i.e.

Boston (zone 5), Chicago (zone 5), and Minneapolis (zone 6), are worse off in terms of annual energy savings by alignment on the whole-year basis. Warmer places, however, i.e. New York (zone 4), Houston (zone 2), and Miami (zone 1), achieve similar efficiency through the whole-year-based alignment and the summer-based alignment. Lastly, alignment by the wintertime temperature turns out to be the worst approach overall, which is completely dominated by the other two approaches at every location.

4.6.2 Interpretation

In order to elaborate on the mechanisms determining the efficiency of the alignment strategy, we superimposed the range of all residents' thermostat preferences (according to Table 8) on the monthly operative temperature for the Building 5 test-case, defined as the average free-running temperature of all Building 5 apartments, for each region (Figure 25). The shaded zone in the center of each plot shows the cooling thermostat range while the shaded zone on the side shows the heating thermostat range, with the upper and lower edges of each of these zones representing the thermostat preferences of the two extreme groups, namely the hot and cold groups, respectively. The cooling thermostat is operated from May to September and the heating thermostat is operated from October to April, which was initially determined by examining the New York weather file data during the initial simulation in Section 3.4. We applied this division of seasons to all regions except the South region where cooling is extended year-long while heating is removed in April and October.

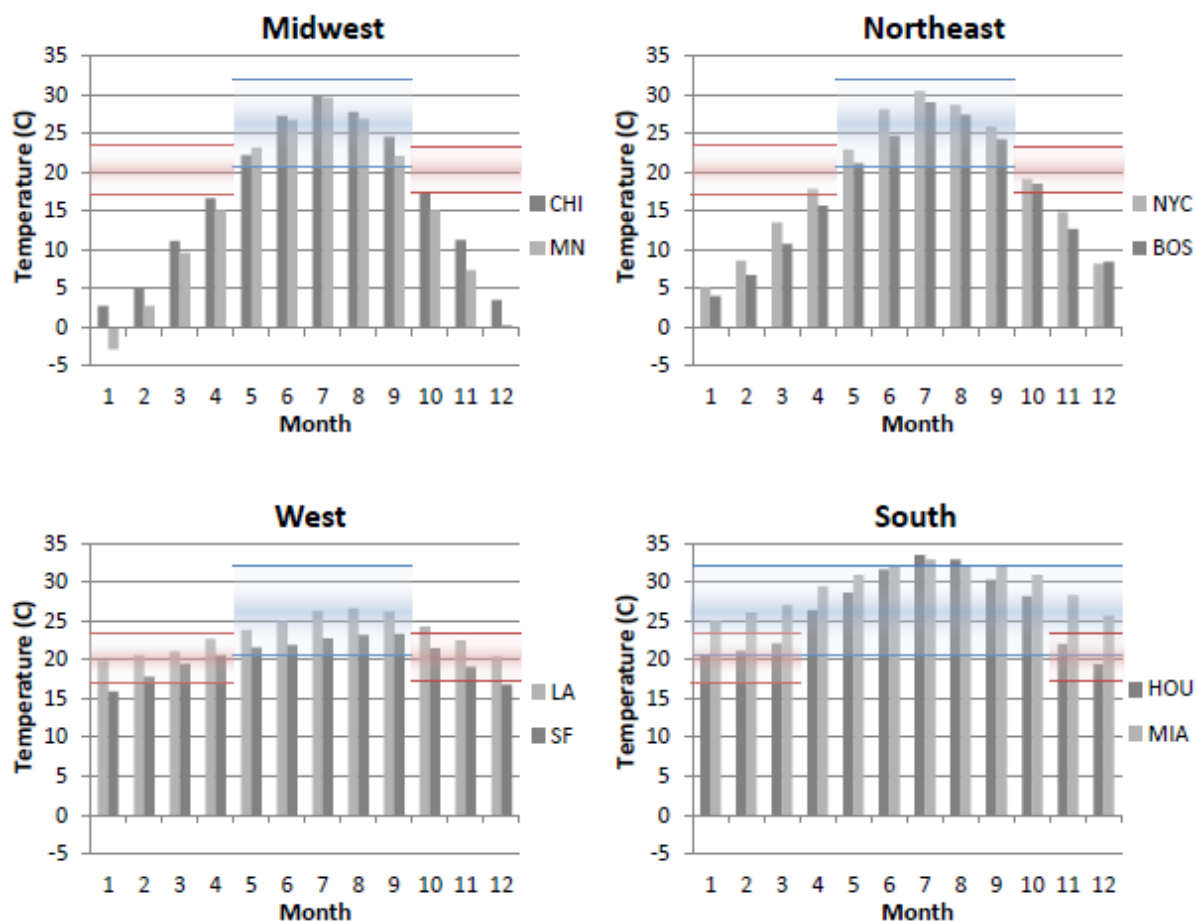


Figure 25. Cross-region alignment comparison

Figure 25 reveals a key insight: whether (and to what extent) space conditioning is required can be indicated by the spatial relationship between the temperature bars and the shaded thermostat zones for each region. Specifically, when the temperature bar is below the lower edge of the zone on the side (e.g. during all winter months at Minneapolis), it means all groups of residents have heating demand; when the bar is above the zone (e.g. October at Los Angeles), no heating is needed even for the residents that have a hot thermostat preference. The opposite is true for the zone in the center in terms of cooling. Thus, when the temperature bar is out of the zone, the relationship between occupant thermostat preference and the unit temperature cannot be manipulated for energy conservation. Conversely, the alignment

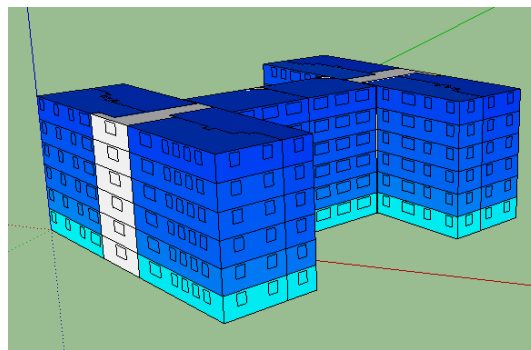
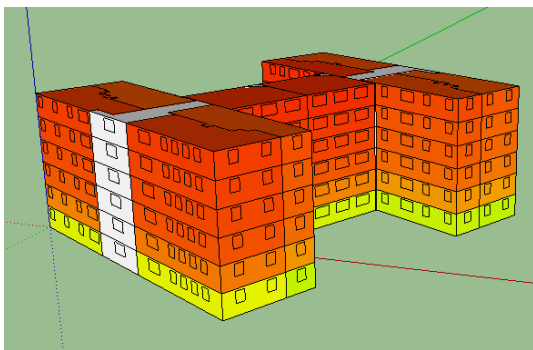
strategy reaches its full potential when the temperature bar is around the middle of the shaded thermostat zones, in which case cooling or heating needs can be minimized or even avoided by taking into account large variances in residents' thermal preferences. Intuitively, such interpretation lies in the proportionality of the heating/cooling requirements to the number of Heating/Cooling Degree Days at a specific location, which is the aggregate difference between the outside air temperature and a defined base temperature. The total overlap of temperature bars with thermostat zones across the year decreases as the location changes from Los Angeles to San Francisco, Houston, and New York, as can be observed from Figure 25. This sequence is consistent with the decreasing savings from alignment at these four places, as displayed in Table 9, and supports the above reasoning. Another notable observation in Figure 25 is the dual demands during several months, especially during the transitional seasons, revealed by the partly overlapped thermostat zones in the South region. This overlap indicates that some apartment occupants require cooling while others require heating, although only a single conditioning requirement exists in each particular apartment. Altogether, we conclude that the alignment strategy is most suited to mild climates, such as California's Mediterranean climate which has warm to hot summers and mild to cool winters, because of the coincidence of the thermostat preference range with the free-running room temperature range over many months of the year.

4.6.3 Strategy Implementation Guidance and Policy Implication

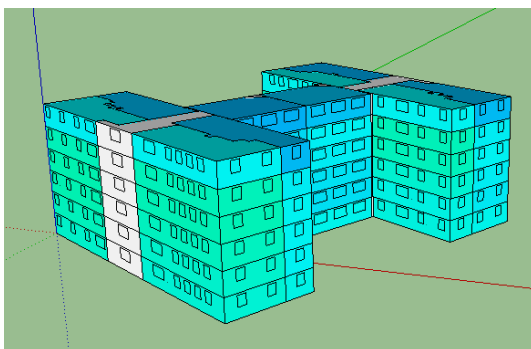
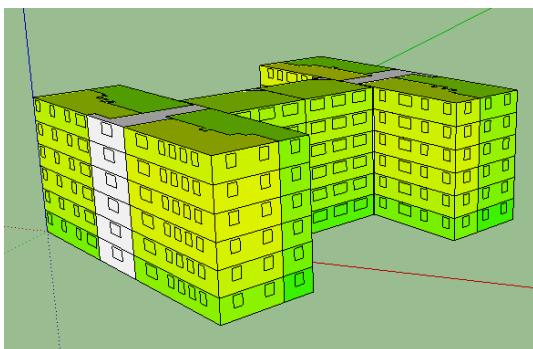
To guide the implementation of ESAS, we visualize the spatial distribution of apartment temperatures in four different cities in SketchUp (Figure 26). We pick the four cities in a manner to represent the whole span of annual alignment savings in Table 9: Los Angeles

obtaining the highest saving (34.7%), San Francisco with the second highest (26.3%), Houston with the third highest (10.0%), and New York representing the average of the moderate-saving-group (4.0%). The four cities are displayed in the decreasing order of their latitudes, with the result that the color becomes warmer from top to bottom except for the hot summer in New York. As seen in Figure 26, the free-running apartment temperature usually decreases as its floor level decreases, with the exception of the ground and top floors. The ground floor is apparently warmer in a cold environment and cooler in a hot environment because of heat transfer reasons discussed in Section 3.4, as revealed by a comparison of New York and Houston. The top floor is noticeably cooler than the floor immediately below it during cool days, including the whole year at San Francisco and the winter at all other locations, because of the roof's direct exposure to the cool air. Additionally, apartments on the north side of the building are cooler than that on the south, east or west sides. The patterns shown in Figure 26 set the foundation for ESAS guidance on a general basis.

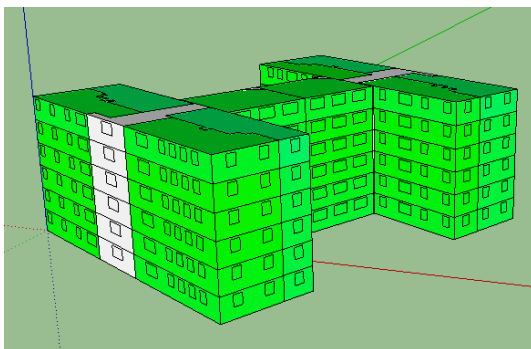
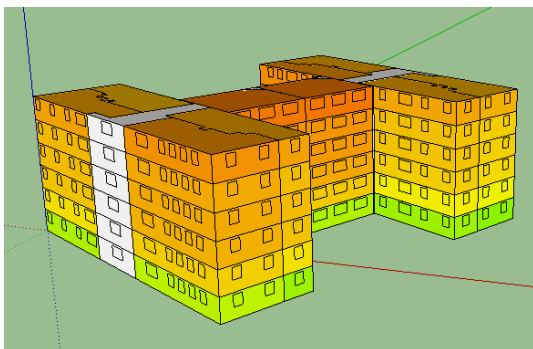
(a) New York



(b) San Francisco



(c) Los Angeles



(d) Houston

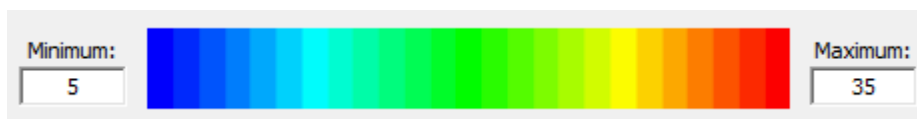
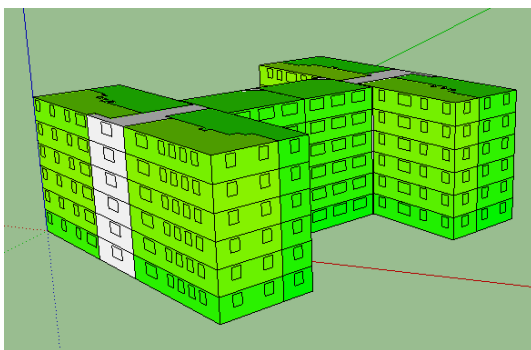
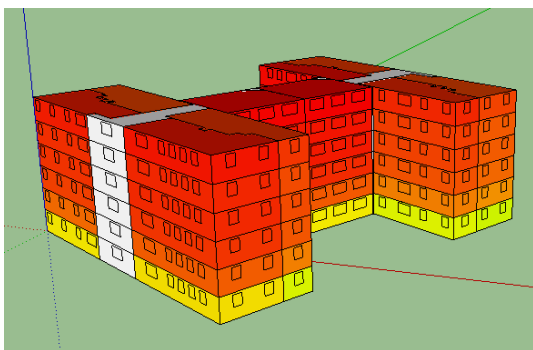


Figure 26. Visualization of unit temperature variation (in Celcius) around noon time in typical summer (left) and winter (right) day at representative locations

The alignment strategy guidance for the four chosen cities, i.e. New York, San Francisco, Los Angeles, and Houston, is presented in Table 10. In the first column, the best period upon which to base the alignment is in parentheses. Correspondingly, the right three columns show the spatial distribution of the average apartment temperature during that period. This distribution chart can guide strategy implementers to allocate tenants to apartments that match their thermal preference category. Supported by the visualization, the spatial distribution is generalizable to some extent across the locations. In this regard, the apartment assignment can be performed as proposed below:

- cold-preferred residents: ground floors;
- cool-preferred residents: top or lower middle floors on the north side;
- mid-preferred residents: middle floors on the north side, or top or middle floors on the east/west side;
- warm-preferred residents: top or lower middle floors on the south side, or upper middle floors on the east/west side;
- Hot-preferred residents: upper floors on the south side.

Table 10. Apartment assignment guidance based on occupant thermal preferences

		S	E/W	N
New York (summer)	Top floor		hot	warm
	Middle floors		↓ warm	↓ cool
	Ground floor(s)		cool/cold	cold
San Francisco (whole year)	Top floor	warm	mid	cold
	Middle floors	hot ↓ warm	warm ↓ mid	mid ↓ cool
	Ground floor(s)	cool	cold	cold
Los Angeles (whole year)	Top floor	warm	mid	cool
	Middle floors	hot ↓ warm	warm ↓ cool	mid ↓ cool
	Ground floor(s)	cold	cold	cold
Houston (summer)	Top floor		hot	warm
	Middle floors		↓ cold	↓ cold
	Ground floor(s)			

For public housing management to implement ESAS, a collection of self-reported thermostat preferences in the housing application process is needed. We suggest integrating this thermostat survey into existing application files or databases. It should be noted that this guideline does not and cannot take into account the influence of specific surrounding conditions [4], so room-installed thermometers may afford customized alignment strategy at each particular place. Other than the thermostat survey and possible usage of thermometers, the implementation of ESAS requires virtually no significant cost to Housing Authorities, and does not involve costs incurred by physical changes to buildings.

In contrast to the low implementation cost, the benefits from applying ESAS could be considerable. For New York City Housing Authority, the utility expenditures are projected to

continue to increase from \$549 million in 2012, accounting for 18% of total expenditures, to \$626 million in 2016 [111]. The 4% energy savings under New York's climate condition means that an approximate \$25 million reduction on NYCHA's annual energy bills can be realized by implementing ESAS in New York City alone. Given the primary energy savings between 2.7% and 34.7% from the cross-region comparison, more substantial monetary savings are likely to be attained in other cities. ESAS also possesses long-time effects if it is adopted in all HUD public housing projects, through assignments at new projects and the dynamic relocation when tenants move in and out at existing projects. The cost-effectiveness can be further enlarged if synergy emerged from a thermostat database which could contribute to understanding the effect of thermostat settings and for deciding other energy-conscious strategies [99].

4.7 Conclusion and Future Research

In the present study, we propose a novel Energy Saving Alignment Strategy (ESAS) that matches the distribution of tenants' thermostat preferences with the indoor operative temperature in public housing to achieve combined maximized energy efficiency and thermal comfort. The case study is Amsterdam Houses, a public housing project in New York City with 1084 units. We firstly obtained the distribution of thermostat preferences from survey data and the distribution of apartments' free-running operative temperature through EnergyPlus simulation, and classified each of them into five categories, i.e. cold, cool, mid, warm, hot. Then we conducted the alignment by assigning each family to an apartment with the same temperature class as the family's preferred warmth class, and compared the simulated energy use with the baseline in which random housing assignment occurs, reflecting the current situation at public housing. We evaluated three alignment methods using operative

temperatures in the summer, winter and year-round, and expanded the test to eight cities representing all four U.S. regions and six climate zones. Results revealed 2.7% to 34.7% primary energy savings from ESAS as compared to the baseline depending on location. The alignment realizes the highest efficiency at mild climates where the preferred thermostat range coincides with the room temperature range. We conclude that the proposed ESAS can yield considerable and long-acting energy savings as well as occupant comfort, with advantageous cost-effectiveness compared with many existing energy saving strategies. In the end, a guideline on performing an aligned assignment is presented to facilitate its implementation.

We have investigated the idea of ESAS in the realm of thermostat management in public housing, but the approach may be useful to various other areas. A direct expansion is for university dormitories, where students have little financial incentive for energy conservation as they are usually not responsible for utility bills. By allocating students to dorms that are in line with their thermal needs, a university can save significantly on energy costs of space conditioning. Another possibility emerges in net zero energy buildings. This aligned arrangement may help strengthen the feasibility of reaching net zero energy by reducing the primary energy payback period and enhancing the CO₂ equivalent saving. In a broader context, ESAS can be integrated into demand side management that aims to reduce the overall energy use and peak demand of buildings, in particular, the direct load control through customer incentive programs.

Some limitations and related extension of the present study deserve future attention. One technical point is that we assume each family has a uniform temperature preference to make the assignment of 1084 apartments manageable. Future research can introduce different

thermostats for bathroom, bedroom, etc., and different preferences of family members, and suggest a more nuanced alignment strategy. Another limitation lies in the possible discrepancy between self-reported thermostat preferences and the actual settings, examination of which may allow future studies to make appropriate adjustments to the design or implementation processes. Additionally, greater focus on leveraging the spatial variation of apartment temperatures and the variability in the way people manage their indoor comfort may bring synergies to other energy programs. Fourthly, we only estimated savings of ESAS on one public housing project; future research should continue testing other projects with different building layouts to verify the strategy's effectiveness and the assignment guideline's generalization. As a step further, emphasis of future research should be made on empirical studies in real public housing and evaluating ESAS' feasibility through policy studies. Apartments in HUD low-income public projects are currently assigned by a computerized system that chooses families based on their place on the waiting list, as well as factors like emergency need. Future research should collaborate with local PHA to gauge the potential for a large-scale implementation. Given the need for development and renewal of policy [112], policy studies should take a deeper look at possible policy measures and their combinations with existing policy and energy efficiency strategies at HUD to ensure a smooth implementation.

Chapter 5

5. CONTRIBUTIONS

The research reported in this dissertation investigated strategies that leverage human-environment systems in residential buildings to boost overall energy efficiency and hence sustainability. Here, the environment subsystem consists of the immediate built environment, taking into account the indoor and outdoor conditions within a network of buildings as well as conditions in the surrounding neighborhood. The human subsystem consists of those living and working in the built environment, whose behaviors, both individually and socially, have an impact on the environment subsystem. The integration and interdependence of the human and environment subsystems, which constitute the core concepts of sustainability science and determine the condition, function, and response of the subsystems individually, as well as that of the system as whole, were the main focus of this research. As discussed in Chapter 1, this framework is considered essential in searching for solutions to reduce energy consumption and its associated greenhouse gas emissions in the built environment.

Building from the holistic framework of coupled human-environment systems, the findings of this research have advanced existing knowledge of emerging energy efficiency approaches and led to the development of novel strategies in this area. In Chapter 2, a study of three closely related factors, buildings, residents and their surrounding neighborhood, at the inter-building level concluded that leveraging neighborhood-contextualized occupant social networks could lead to improvements in energy efficiency performance at the inter-building

level that are comparable to the efficiencies gained through typical building retrofits. This finding indicates that integrating buildings and occupants as networks could have a major impact on neighborhood-wide energy efficiency. Chapter 3 takes these concepts further, focusing on ways to utilize the synergy between building networks and peer networks to develop inter-building level energy management strategies. The energy savings resulting from integrating the two networks was found to actually exceed the sum of the energy savings that could be achieved through leveraging either the building network, in the form of physical interventions that can positively influence adjacent buildings, or the occupant network, where eco-feedback systems are used to disseminate energy conservation behaviors, alone. The findings of these two studies culminated in the development of the work reported in Chapter 4, which proposes an Energy Saving Alignment Strategy (ESAS) that aligns occupant thermostat preferences with an apartment's thermal environment to maximize comfort satisfaction and, accordingly, energy savings from space conditioning in multi-family residential buildings.

Reaching beyond the scope of existing energy efficiency strategies that are produced with a partial consideration of the coupled human-environment systems, the strategies proposed in the dissertation overcome the shortcomings of existing approaches in a number of ways. First, by internalizing the impact on related entities in an interconnected system, these strategies achieve a network-wide energy efficiency that simply cannot be attained using the traditional single-unit-(i.e., building or apartment) focused perspective. Second, the proposed strategies offer substantial cost advantages compared with the considerable investment required for physical renovations, and the effects could be far longer-lasting than

temporary behavioral campaigns as they are based on point-in-time methods, where the resulting savings are robust and predictable. To add to the above beneficial attributes of the proposed strategies, guidelines are provided in Chapters 3 and 4 to facilitate their evaluation in other contexts and their implementation in practice to scale up their gains in energy efficiency.

The integrative network perspective adopted in this dissertation might also have a broad theoretical impact on the work of others seeking to achieve significant reductions in energy usage. The energy conservation context used here to examine the potential for network-wide efficiency improvements is an ideal class of network problem that directly addresses the call from the National Academies to study network structure, function, and dynamics in conjunction with modeling efforts in order to advance our fundamental understanding of network dynamics and associated applications [87]. This dissertation also serves as an exemplar of the way interdisciplinary research at the interface between the natural and human sciences can produce exciting and innovative new ideas and approaches in the realm of building energy efficiency. Concepts and methodologies from a range of multidisciplinary fields were utilized in the course of this research, including building energy simulations, social network analyses, artificial intelligence, empirical household surveys, and policy studies. Taken together, the methodology presented in this dissertation supports others seeking to utilize these approaches, especially as part of an interdisciplinary synthesis, to create more powerful and suitable tools for use in energy efficiency and sustainability studies.

Individual Chapter Contributions

This section discusses the contributions of each research chapter in more detail.

***Chapter 2: The impact of place-based affiliation networks on energy conservation:
A holistic model that integrates the influence of buildings, residents and the
neighborhood context***

Prior studies explored, separately, the influence of buildings' mutual impacts [4] and occupant social behaviors [42] on energy consumption in order to build a better understanding of the role of building networks or occupant networks on building energy conservation. Existing studies had revealed that the neighborhood context plays a critical role in the strength of occupants' social networks [45, 50], and that their resultant place attachment, or human bonding to the physical environment, supports pro-environmental behaviors [51, 52]. However, there are no reports of studies that have attempted to evaluate the integrated impact of these multiple effects and quantify potential energy savings to be gained from renovating buildings and leveraging occupant social networks derived from neighborhood affiliation.

In Chapter 2, a holistic model to evaluate built environment energy efficiency performance is established that consists of three components: building networks, occupant social networks, and the surrounding neighborhood facilities. This is the first such study to model all three components together. As part of the model, I consolidate the logic chain showing that place attachment from frequenting neighborhood facilities can generate social networks among occupants, the closeness of which will encourage pro-environmental behavior. This integrated model reveals that leveraging place-based social networks by means of eco-feedback systems could lead to improvements in energy efficiency performance at the inter-building level that are comparable to the efficiencies gained through typical building retrofits. This theoretical finding has a significant practical contribution: social networks

among residents should be harnessed by community planners in inter-building level energy management beyond physical green design to achieve the highest possible level of building energy efficiency. This is due to the larger unexploited potential saving impact of harnessing the power of a close social network, which can extend beyond physically efficient buildings, and also because such encouragement of energy conservation has the potential to be more cost-effective than physical renovations.

Chapter 3: Network synergy effect: establishing a synergy between building network and peer network energy conservation effects

Chapter 3 extends the research findings reported in Chapter 2 to show that network effects on energy consumption exist when buildings are examined within physical networks (i.e. they exhibit an inter-building effect) [4] and when individuals influence the energy use of their peers (i.e. a peer network effect) [42]. Work in the chapter explores the synergy that may result from an interaction between these two effects to create even greater aggregate energy savings. Both computational and empirical approaches are used, sequentially, to discover and then demonstrate such potential synergy. For a case uncovered by the simulation process where a less energy efficient option for a single house produced higher efficiency in neighboring houses, a neighborhood empirical survey revealed a phenomenon where knowledge of the impact of alternative retrofit options on each building in the network, combined with strong interpersonal relationships between the homeowners, can drive decision-making toward aggregate optimal outcomes. The interaction of inter-building and peer network effects was found to result in energy savings that exceeded the sum of the energy saving potential induced by either one of the effects alone. It is here in Chapter 3 that I define the term Network

Synergy Effect to represent this additional energy efficiency. In practice, Chapter 3 strengthens Chapter 2's findings and their implications to stress not only the importance of enhancing the interpersonal closeness among residents, but also the utility of carrying out energy saving interventions that capitalize on such social networks. In particular, this study emphasizes the importance of leveraging the interaction between networked occupants and networked buildings in the neighborhood environment through community-based social marketing to promote energy conservation in homes.

Chapter 4: Energy saving alignment strategy: achieving energy efficiency in urban buildings by matching occupant temperature preferences with a building's indoor thermal environment

Limitations to existing energy savings strategies may impede their application when efficiency and sustainability are valued. Most interventions that involve physical renovation are costly and time-consuming to implement and maintain; furthermore, while some behavioral strategies can lead to energy conservation without the expense of added infrastructure, their effect can be transient [6]. In light of the wide spread of occupant comfort preferences and the recent tendency to organize building operations around the optimal combination of thermal comfort and energy savings, Chapter 4 proposes an Energy Saving Alignment Strategy (ESAS) for multi-family residential buildings that assigns occupants to apartments whose indoor temperatures are best aligned with their thermostat preferences in order to maximize thermal comfort and, accordingly, reduce the energy required for space conditioning. After testing a case study of a public housing complex in New York in various climate environments, the ESAS was found to yield considerable energy savings compared

with apartment assignment practices that neglect occupant thermostat preferences, with a consequent improvement in cost-effectiveness and a long-lasting influence.

The innovation embedded in ESAS is beneficial and widely applicable in a number of different practical areas. For example, by allocating students to dormitories that closely match their thermal preferences, universities can save significantly on space conditioning energy costs through such a thermostat management strategy. This aligned arrangement may also help extend the period of net zero energy, thus reducing the primary energy payback period and enhancing the CO₂ equivalent saving. For a broader contribution, ESAS can be integrated into demand side management approaches that aim to reduce the overall energy use and peak demand of buildings.

Chapter 6

6. LIMITATIONS AND SUGGESTED FUTURE RESEARCH

The primary focus of this dissertation has been to improve the energy efficiency and sustainability of the built environment. The research has attempted to capitalize on the integration and interaction of human-environment systems to discover and evaluate related strategies that could contribute to this effort. However, although such research is beneficial in moving toward the goal of sustainability, it is not without its shortcomings.

The main limitations lie in the fact the results are limited by data availability, specific context, and research scope. The accuracy of Chapter 2's quantitative results is highly dependent on the quality of the residential experimental data and the availability of relevant demographics. In Chapter 3, factors such as the choice of urban area, the number of buildings, the infrastructural properties, and the nature of the retrofits that could be undertaken all meant that the results were focused on a specific context. The survey results could also have been biased by the specific community studied and the relatively small sample size. Although the integration and interaction of the building and occupant networks were identified for particular scenarios in Chapters 2 and 3, it is not yet possible to generalize these findings to other contexts. Similarly in Chapter 4, the potential savings that could be achieved by applying ESAS were only estimated for a single public housing project and it remains for future research to continue testing the new model for other projects with different building layouts to verify the strategy's effectiveness and the assignment guideline's generalization. Another limitation lies in the compatibility of various sources from which data were drawn

for this multidisciplinary research project. In particular, in Chapter 2 the assumption is made that social networks' influence on energy use is similar in university dormitories and household communities, yet the dorm residents might not behave in the same way as the household residents. However, the analogy is sufficient for the purposes of this initial attempt to examine the potential role of social networks on neighborhood energy conservation.

Future researchers can extend the research scope of this dissertation by seeking evidence that validates or adjusts the presented framework, as necessary, or utilizes it in more systematic explorations of different aspects of energy conservation. Empirical studies, by means of survey or residential experiments, are recommended to test the proposed strategies on energy conservation in real neighborhoods, for example by verifying the effect of place-induced affiliation networks among residents, as analyzed in Chapter 2. For the study presented in Chapter 3, an immediate future extension is to examine the network synergy effect in a variety of contexts and retrofit options in order to fully realize the applicability of the network synergy effect in encouraging large-scale energy reduction. To develop the model presented in Chapter 4, future researchers could collaborate with a local Public Housing Authority to gauge the potential for a large-scale implementation of the proposed Energy Saving Alignment Strategy. Given the need for the development and renewal of policy in the arena of building energy consumption [112], more detailed policy studies are necessary to examine possible policy measures and how these will interact with existing policy and energy efficiency strategies. In its entirety, a future direction is to reconsider the dissertation's methodology, which initially focused solely on single-family and multi-family residential buildings in commercial and institutional buildings, to create an across-the-board suite of

applications.

The use of a holistic network perspective is suggested for future endeavors that does not only include building clusters, interconnected residents, and surrounding environments, but also the mutual influence of different energy strategies. Such a view would be particularly advantageous for efforts to pursue better aggregate energy efficiency and reductions in greenhouse gas emissions. For example, in the light of the findings reported in Chapter 4, greater attention should be paid to leveraging the spatial variation of apartment temperatures and the variability in the way people manage their indoor comfort such that the knowledge and thermal improvement obtained can be combined synergistically with other energy programs. Future research should systematically compare the energy efficiency gained from strategies based on a holistic perspective with that achieved by traditional physical methods of building retrofits in terms of cost-effectiveness and feasibility to guide the emerging trend in harnessing human-environment systems to boost energy sustainability.

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