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Methodologies for Studying Human-Microclimate Interactions for Resilient, Smart City Decision-Making

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ABSTRACT: Creating sustainable, resilient cities requires integrating an understanding of human behavior and decision-making about the built environment within an expanding range of spatial, political, and cultural contexts. Resilience—the ability to survive from and adapt to extreme or sudden stresses—emphasizes the importance of participation by a broad range of stakeholders in making decisions for the future. Smart cities leverage technology and data collected from the community and its stakeholders to inform and support these decisions.

Energy usage in cities starts with people interacting with their environments, such as occupants interacting with the buildings in which they live and work. To support city stakeholders as they develop policies and incentives for improved resilient energy utilization, researchers also need to consider microclimates and social dynamics in addition to building-occupant interactions. Sustainable design of the urban built environment therefore needs to expand beyond buildings to include near-building conditions. This requires investigating multiple scales and types of data to create new methodologies for design and decision-making processes.

This paper presents a conceptual framework and interdisciplinary research methodology that integrates models and data-driven science with community engagement practices to create partnerships between university researchers, city officials, and residents. Our research team from design, natural sciences, data science, engineering, and the humanities presents a first example of a transformative method of data collection, analysis, design, and decision-making that moves away from hierarchical relationships and utilizes the expertise of all stakeholders.

Keywords: urban energy modeling, community engagement, sustainable architecture, data models

INTRODUCTION

With increasing climate variability, extreme weather events, and rising urban populations, city stakeholders struggle to develop policies that protect the integrity of urban food, energy, and water systems, particularly for marginalized populations (PSC 2015, C40 2015). The existence of food deserts, energy poverty, and water vulnerability are likely to increase with global climate change (C40 2015, Cathleen et al 2016, OECD 2011), and city stakeholders face significant challenges to meet increasing resource demands, economic stratification, and environmental uncertainties while staying within budget constraints. As cities work to create stakeholder-relevant and cost-effective policies, they recognize a crucial need for better data-driven tools to assist decision-making. The emerging interdisciplinary field of urban data science is thus uniquely positioned to help solve one of the greatest societal problems of the century.

Our research team’s long-term goal and vision is to develop more useable and stakeholder-driven support for sustainable city decision-making. This vision will produce a first-of-its-kind integration of data-driven spatial, economic, and behavioral models that merge human-built environment interactions with energy resource performance predictions. Integrating human behavior and decision-making data into computational thermal-physical models of the built environment will support cities in creating more stakeholder-relevant and equitable environmental policies and practices.

Computational models can predict and propose changes to energy systems that are efficient and effective. Without input from human decision-makers, however, these models risk irrelevance because they do not take into account factors upon which many city and individual decisions are made, such as money, values, and politics. For researchers to develop effective models that assist city decision-making, they must engage with the staff, elected officials, and residents of that city in order to understand local priorities, interests, and biases—a set of conditions that require additional attention to ensure equitable resource access and policies.

This paper presents a conceptual framework and interdisciplinary research methodology that integrates models and data-driven science with community engagement practices to create partnerships among university researchers, city officials, and residents. Within this framework, agent-based modeling tests building retrofit scenarios developed with urban energy models. Engaged community work with marginalized residents and crowdsourcing data collection refine the model inputs and scenarios while data models expedite
the evaluation of large data sets from a variety of sources needed to compute urban energy models based on human behavior (see Figure 1).

![Conceptual framework integrating urban energy, agent-based models and mathematical data-driven models with community engagement practices](image)

**Figure 1:** Conceptual framework integrating urban energy, agent-based models and mathematical data-driven models with community engagement practices

**RESEARCH PARTNERSHIP THROUGH COMMUNITY ENGAGEMENT**

To develop the system described above, the research team is partnering with the City of Des Moines, Iowa, a mid-sized Midwestern city with focus on a resource-burdened section of the city. This area was targeted in 2013 to begin neighborhood revitalization processes and later developed a local community organization, a “coalition of partners and residents working together to revitalize three neighborhoods” (Viva East Bank). At the same time, increased value is being placed on energy efficient buildings and community engagement, as articulated in the city’s current strategic plan (Lyle Sumek Associates, Inc. 2015). The projected outcome of this partnership is an improved utilization of data related to energy efficiency to create programming and policies that support neighborhood revitalization as well as resilient energy systems.

Within this framework, energy simulation and modeling tools are often used to support decision-making on energy utilization. Consideration of the human behavior effects on energy utilization must also be considered. This methodology uses a human modeling technique known as agent-based modeling (ABM) to capture how human (agent) decisions result in emergent behavior of a community of people. Preliminary work (Krejci et al 2016) has been done to develop an agent-based model to represent individual homeowners making decisions on home weatherization. This ABM tests building retrofit scenarios integrating results with an urban energy model (UEM). In future work, crowdsourcing data collection techniques can be used to refine both the model inputs and scenarios while data models expedite the evaluation of large data sets.

To create recommendations that go beyond efficiency and make implementation likely, engagement with community stakeholders needs to move beyond gathering input data for an already-planned specific project. Instead, it needs to involve residents as partners in assessment and decision-making. To this end, our team employs participatory design, storytelling, and social science research—particularly Participatory Action Research (PAR)—to learn about the concerns and priorities of neighborhood residents, city staff, and elected officials. Because project success depends not only on model efficacy but also relevance of its findings, it is important that we develop relationships that allow local stakeholders to share decision-making with city officials (Arnstein, 1969).

PAR moves away from traditional research methods in which researchers do not seek to influence their subjects, focusing instead on creating an interactive partnerships that involve joint problem-solving, goal-setting, and value-sharing (Sanoff, 2000; Kemmis, McTaggart, & Nixon, 2014; Bradbury, 2015). As described by Wisner, Stea, and Kruks (1996), a PAR model reflects the view that the people using an environment have expertise about that environment that differs from, but is equal to, that of credentialed experts and is therefore a critical component of the research. Participants identify issues, determine what and how information will be collected, and evaluate results.

In the case of the built environment energy model, stakeholders provide information about what should be modeled and feedback on modeling outcomes to further refine the model. Ideas generated from successive feedback loops, subsequently help inform what programs and policies the city needs to develop to improve neighborhood energy efficiency. As the entry-point for developing community relationships, our team is partnering with a local high school organization with interest in community service and leadership. Our team selected to begin our work with youth because all three East Bank neighborhoods have large youth populations and neighborhood plans identified supporting youth as a priority (Iowa State University Planning Team, Capitol East Neighborhood Association, and City of Des Moines. 2014; Martin Luther King Jr. Park Neighborhood Association, 2014). This partnership establishes credibility with adult community members.
and furthers already-established goals to create opportunities for youth engagement.

In keeping with PAR-related strategies for community empowerment, the youth group has played a central role in devising our team’s work in the community. The youth have helped shape our community engagement efforts through their interest and leadership in transforming an under-used middle school garden into a community gathering place. The youth’s work with this garden is proving beneficial to both the community and the research team, due to partnerships between the youth organization, the high school and middle school, the research team, and several community-based organizations. From these partnerships will occur a series of community days at the garden during the coming months that will include not only discussion of sustainable urban food production but also issues related to energy efficiency and home weatherization. Through the youth’s ideas for the garden and the outreach efforts, our team has developed a tactic for engaging the broader community: we call such productive, community gathering spaces “action hubs”— hubs that engage a range of neighborhood interests by reactivating existing neighborhood spatial assets.

In preparation for the community days, the researchers and youth are collaborating to create data collection mechanisms to solicit feedback about residents’ behaviors, motivations, needs, and awareness of available energy efficiency programs. These mechanisms provide information for our model that integrates the agent-based model (ABM) and urban energy model (UEM). In the future, these community days can also be venues for providing feedback on scenarios created by this integrated model, which will enable further model refinement and ultimately provide options for city programming and policies. At the same time, we will be meeting with, and collecting feedback from, city staff and elected officials.

**INTEGRATION OF AGENT BASED MODELS WITH URBAN ENERGY MODELING TOOLS**

As a central component to involve community and city in data collection and decision-making, the research team is integrating an ABM and an UEM to determine human-microclimate interaction on a neighborhood scale. The ABM connects the goals and constraints that drive occupant behavior with the physical processes of built environment systems. This model is, in turn, integrated with an urban energy model using Rhino Urban Modeling Interface *umi* (Rose et al., 2015)). These computational models explore and predict interactions between community members and their environment. As a sample case, one of the neighborhoods was selected (See Figure 1). This block includes 29 individual buildings on either side of the central street.

**Urban Energy Model**

To generate the comparative data required for the ABM, a detailed energy model of the neighborhood shows the potential energy savings resulting from residents’ decisions to weatherize their homes. Rhinoceros 3D and the *umi* plugin from Massachusetts Institute of Technology (Reinhart, 2013) were used to create the digital model of the block and then simulate the energy performance of each house within the selected area. *umi* offers the ability to edit the material assembly of individual houses in the neighborhood, facilitating the testing of the potential impacts of such weatherization strategies as re-caulking windows to decrease air infiltration or adding spray insulation in unfinished attics to prevent heat loss during the winter. The model creates datasets that represent the pre- and post-weatherization conditions. The one block area of the neighborhood being analyzed was selected because of the similarity of the buildings in both use and construction while still representing a large range of building sizes. The 29 buildings analyzed in the energy model are all residential and built with wood-frame construction (see Figure 2).

**Figure 2: Sample model visualization of energy consumption in a neighborhood**

The first step in developing the energy model was to model the physical geometry of the neighborhood with Rhinoceros 3D. Spatial information used to model building footprints, streets, sidewalks, and lot boundaries was extracted from Geographic Information Systems (GIS) maps that are maintained by the City. These maps include building footprints for each building and indicate which buildings are more than one story high, making possible the refinement of the individual 3D models. The second step was to use the information available on the County Assessor’s database (Polk County Assessor, 2015) to extract the building related data needed to build the simulation model with *umi*. This data includes building address, parcel number,
number of building stories, date of construction, construction type, and number of separate residences per building. An ID system for each house was derived from the parcel number of each lot and used to cross reference information between the Rhino 3D UMI model and the assessor’s data. The 3D house models were created by extruding each building’s footprint to the given roof elevation included within the GIS data and then manually edited later using measurements from the assessor’s floor plans to reflect more accurately the true configuration of the houses. This step is important because the umi energy simulation analyzes each structure based on the volume of a given structure, and most multiple story houses are only “full height” at a certain percentage of their floor area (see Figure 2).

Agent-Based Model
Agent-based modeling (ABM) has been particularly useful for understanding and managing multi-disciplinary systems with many interacting elements (Axelrod, 1997; Bonabeau, 2002). ABM is a computer simulation technique that replicates the behavior of individuals (agents) and their interactions with the environment and other agents (Axtell et al., 2002). In buildings, individual agents are building occupants, and the occupant’s environment is the building interior. ABM simulates the unique decision-making behavior of individual occupants and then shows how the overall, complex building behavior emerges as a result of those behaviors (Klein et al., 2012). The decision-making process of individual occupants explains behavior, intentions, and actions in response to environmental stimuli (Gaudiano, 2013). Behavioral intentions are the occupants’ goals for eliminating undesired environmental conditions. Occupant actions initiate changes in the environment. Behavioral intentions define ABM structure to evaluate the impact of various occupant actions in response to a number of different physical environment stimuli factors (Kalvelage, Dorneich, Passe, & Krejci, 2016).

The ABM in this research has been developed using NetLogo (v. 5.0.2). The model is designed to assess the neighborhood-level effects (in terms of total energy consumption) of individual residential building occupants’ decisions with respect to weatherization activities. The model contains 29 autonomous agents, each of which represents a household in a specific block of the selected neighborhood in the Midwestern city. Based on the assumption that weatherization decisions are made at the household level, each agent may represent an individual or a collective of individuals (e.g., a family). The model is dynamic, and state changes in the ABM (e.g., the percentage of weatherized houses) are updated at the end of each monthly time-step.

At the beginning of each time-step, the umi (described above) is used to evaluate each household’s energy consumption. This data is then passed to the ABM, and the energy costs for each household are calculated. These costs partly inform each agent’s decision about whether or not to pursue weatherization for its home, and if so, what the appropriate level of investment (e.g., filling gaps under doors, adding insulation, replacing windows) should be. The agent evaluates the expected energy cost savings from weatherization as well as the expected payback period. As in reality, it is possible for the agents’ decisions to be informed by incomplete or incorrect information. For example, based on the demographic data for the neighborhood, it is assumed that all 29 agents are eligible to receive financial assistance for weatherization via subsidized programs. Such programs should act as clear incentives for weatherization. However, agents’ knowledge of weatherization programs is assumed to be limited – they may be entirely unaware that such assistance is available, or they may not understand what the eligibility requirements are. The agents’ perceptions are also a factor – they may be overwhelmed by the application process and decide not to apply. As a result, they may not include financial assistance in their comparative cost evaluations.

While energy cost savings are perhaps the most apparent driver for weatherization decisions, another critical component is the social network in which each household is embedded. Previous research has shown that social interactions and information sharing about energy conservation are the largest determinants of households’ decisions to weatherize (Southwell & Murphy, 2014). To capture the complexities of these influences, the ABM incorporates the social networks that exist among the household agents. Such networks may be based on geographic proximity (e.g., the connections between neighbors) and/or shared interests and cultural values (e.g., via church or community centers). The likelihood that interactions and information-sharing will occur between a pair of agents, as well as the perceived accuracy and persuasive value of the shared information, depends upon the strength of their social connections.

At the end of each monthly time-step, after all agents’ weatherization decisions have been made and any weatherization activities have been implemented, the ABM sends this information back to the energy model. The energy model then incorporates any post-weatherization updates for each household. When the energy model calculates energy expenditures for the following month, these updates will be included and will yield feedback to the agents in the ABM.
**umi-ABM Experimentation**

The objective of this experimentation is to evaluate the effect of individual building weatherization actions on the energy usage of the neighborhood. umi was used to assign each house a simulation template that reflects the construction type and condition of the house, which is translated into thermal performance (R-value) and infiltration rate (the rate at which a given structure allows conditioned air to exchange with unconditioned outdoor air). These characteristics have significant impacts on energy consumption.

To create a comparative dataset, the energy model needs to represent pre- and post-weatherization conditions. Using infiltration rate and thermal resistance as the target impact areas, the baseline file uses the ASHRAE minimum performance requirement for attic insulation within wood framed attic construction which is a 0.15 meter thick layer of fiberglass batt insulation and a 0.12 meter thick layer of polystyrene insulation. The total R-value of the roof assembly is 8.55 m²·K/W. The post-weatherization file doubles the thickness of both layers to 0.3 meters and 0.24 meters respectively, increasing the R-value to 16.04 m²·K/W. The assumed air infiltration rate for the existing structures used in the baseline template is 0.75 air changes per hour (ach), and the post-weatherization rate is 0.25 ach. Combined with a historical weather file (TMY3/EPW) for the location (DOE 2016), the model simulates energy performance of each household on a monthly basis with this performance divided into subcategories such as heating, cooling, and lighting. The simulation is run twice, applying each template to each of the 29 houses on the block. The two comparative data sets were exported to the ABM and were used to inform agent weatherization decisions. Preliminary results from the ABM indicate that a recency effect, a decision bias indicating that humans are more likely to remember and be influenced by recent experiences than those in the past, can yield low adoption rates among agents. Expected energy cost savings from weatherization (and therefore motivation to weatherize) are considerably lower in summer months.

Therefore, if a long lag exists between the impetus to weatherize (i.e., cold weather and high heating bills) and the ability to act (e.g., receiving approval for financial assistance), the perceived value of weatherization diminishes, and few agents follow through with implementation. However, the effect of this recency bias on real-life occupant weatherization decisions has not been established. To ensure the ABM’s validity, empirical human behavioral data must be collected, analyzed, and incorporated into the model.

**REFINED DATA COLLECTION OF HUMAN BEHAVIOR THOUGH GAME-BASED DATA COLLECTION**

Empirical data from the community engagement methods with the youth provides crucial input to the model, but an ability to break down resident decision-making processes into time-steps that occur within situations invoking, for example, extreme weather contexts will provide useful, contextualized data regarding human behavior. To this end, our team has devised an energy game.

The game, played online, will provide data regarding “human sensing”, behavior, perception and activities specifically related to energy consumption and saving as well as data that can be analyzed in increments of the decision-making process. This “soft data”, cannot be measured easily through either quantitative means or standard engagement processes because even the latter, though it may involve decision-making, cannot break down the process of this act into easily recognizable steps. To address this, the contextualized and time-step focused data from the game will be combined with other qualitative data from work with residents as well as measured, quantitative data and aims to improve the quality of simulation and modelling with umi and ABM.

Our approach to the game is based on the crowdsourcing concept—that people living in the community possess the most profound knowledge about their daily routines and preferences related to energy. Crowdsourcing, first defined by Howe (2006), is a “type of participative online activity in which an individual, an institution, a non-profit organization, or company proposes to a group of individuals of varying knowledge, heterogeneity, and number, via a flexible open call, the voluntary undertaking of a task” (p. 197, Estellés-Arolas & Ladrón-de-Guevara 2012). Our approach is based on the conceptual and implementation design of a crowdsourcing data collection energy game. The game aims to attract a variety of different users/players through its user-friendly and fun game environment, engaging characters, motivational tasks, challenges, and stimulating rewards. The main goal is to provide an immersive tool that enables users/players to interact, learn, and build a community interested in learning about energy, energy consumption and saving while competing and collaborating with other members of the community to reach community goals.

Our energy game introduces a variety of housing typologies and house material characters. The players can learn about these materials and their effective uses. The game integrates questions to which players can respond while solving a set of specific energy tasks. They can build a community in which they exchange, compete, collaborate, and compare their gameplay...
results. A primary goal of this tool is to visualize and simulate different life situations and observe how the user/player reacts and makes decisions. Under the what-if simulated scenarios, users select solutions to solve climate/thermal comfort-related events including extreme heat, snowstorms, or broken windows. The data sets gathered by the game will document human behaviors regarding energy conservation, human/building interactions, and building conditions, as well as changes in behavior/decision-making based on learning.

The data collected from the game will document decision-making patterns of community residents in order to refine the ABM. Because the online game simulation has been constructed to trace decision-making patterns within contextualized situations, the team can observe what, how, and in what sequence players choose options and whether or not these options are chosen more often after playful learning opportunities are introduced. The games will: 1) Detect and identify significant patterns in human behavior, providing information for design of agents’ personas in the ABM and their deliberation mechanisms; 2) Observe behavior differences at different levels of the game simulation, comparing human behavior from the first level with behavior from subsequent levels that include learning tools designed to enable players to understand novel problem-solving options.

The energy-crowdsourcing game will be offered online and on mobile devices to reach as many individuals as possible. The hypothesis is that the implementation of a crowdsourcing game for occupant interaction and near building environment data collection will, through direct experience of the built environment and “human sensing,” improve the umi and ABM models input for decision-making and problem-solving as well as increase participation.

NOVEL PROCESSES FOR DESIGN THROUGH COMPLEX DATA MODELING:
In addition to refining the building’s occupant behavior and near building characterization, novel methodologies for integrating disparate and massive data sets are necessary to process the large amount of disparate data while combining traditional mathematical models with models that involve human factors. To verify the ability that pure mathematical data models can indeed be utilized to predict energy performance data, the team developed a mathematical predictive modeling formula. The initial prototype examines a four-year energy performance database from a net-zero passive solar house to mathematically determine which environmental factors are the most crucial energy performance indicators.

The energy performance data set was collected from sensors placed in the solar house (EPSCoR 2016) to monitor the environmental condition, thermal and electric energy consumption, and solar thermal and electric energy generation of the house. The sensors can be classified into two categories. The first category of sensors collected the environmental condition data such as temperature, relative humidity, and illumination luminosity at various locations. The second category of sensors collected data related to the energy (electricity) used and generated by the house. The frequency of data used is one minute, and the first model focused on summer air conditioning electricity consumption in 2015. The purpose of this study is to identify key factors related to energy consumption. Key data features selected for the data model were outdoor temperature, outdoor relative humidity, indoor temperature, indoor relative humidity, wind speed, and fitted relative humidity levels. A newly built humidity levels feature was built to fit a linear model that could explain the air conditioning electricity consumption (see Figure 3).

Since there are strong linear relationships between the predictors, the differences between the indoor and outdoor temperature was used rather than the indoor temperature and relative humidity directly. Since the estimated humidity level is also linear to the temperature, the dew point was deducted from the outdoor temperature before fitting the model. Figure 3 shows the use of the model for four days in September 2015. The blue plot shows measured data, while the red plot shows the fitted value of electricity consumption using the mathematical model with only the filtered data using only the six predictors. The model captures most of the information without considering the time dependency and can be used in combination with weather forecasts and microclimate data to predict energy consumption for this particular building.
CONCLUSION
At each stage of the project, the research team considers how the built environment can be better constructed to support its human users. By partnering with community stakeholders through Participatory Action Research methods, the research team is seeking to build trust, encourage partnership, and treat stakeholders as fellow knowledge-producers who partner with the team to create more relevant research that can more swiftly translate into local actions and policies. Integrating crowd-sourced human behavior data will refine data collection, while mathematical data models will refine the near building environment and develop microclimate databases.

After conceptualizing this integrated data-driven framework, the team will now test the integration of the data-driven model with urban microclimate measurements, utilizing the game prototype to collect data on energy-related human behavior.

The data collected, processed, and modeled in all three integrated steps will only be actionable by the stakeholders if it can be visualized and manipulated in a way to support the stakeholder decision-making process. Therefore it is essential to enhance the data-driven decision support through visualization and thus close the loop by enabling stakeholders to inform decisions and communicate results of the massive and disparate data collected.

In combination, our methodologies aim to make communities and cities full partners in the scientific and design processes, improve data analysis, and enhance the use of data in participatory decision-making. This combination aims to empower and enable cities to better mitigate future climate impacts through energy conservation.

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