



Impact and Cost Analysis of Thermal Load Electrification Measures using Automated Urban Building Energy Modeling in Ithaca, NY

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Abstract

Building decarbonization is an urgent, cross-disciplinary challenge. Holistic urban building energy models (UBEM) could enable planners and municipal government to see the bigger picture and allow for data-driven and community-engaged planning. However, UBEM adoption remains rare, especially in smaller cities, due to technical complexity, lack of data availability, and data sharing on building stock properties and energy use. This paper describes a fully automated bottom-up UBEM simulation approach that fuses geospatial municipal building records, utility billing data, and DOE BEM-derived templates for rapid and building-specific energy scenario simulation using a lower-order 5R1C model. The methods for data fusion, simulation, and result post-processing were tested successfully on a small city decarbonization case study, demonstrating feasibility and accuracy for multi-objective/stakeholder decision-making methodologies to accelerate building stock decarbonization.

Introduction

The UNEP 2022 finds that the building and construction sector accounted for over 37% CO₂ emissions (UNEP, 2022). Building decarbonization is an urgent, cross-disciplinary challenge that requires our immediate attention to limit the adverse effects of climate change. Holistic urban simulation models, often called digital twins, are game changers for decarbonization. They enable modelers to see the “bigger picture” and allow for data-driven and community-engaged planning. However, adoption remains rare due to open questions on reconstructing building properties and a lack of scalable and integrated software for data management, simulation, and multi-objective decision-making. This paper introduces and implements a scalable and automated methodology to generate and calibrate unique building energy models that can be simulated as low-order (5R1C) (ISO, 2008) and state-of-the-art multizone EnergyPlus urban building energy models (UBEMs) to create a holistic geospatial planning tool or “digital twin” for small and large cities in Upstate NY. We demonstrate model accuracy where billed energy use data is made

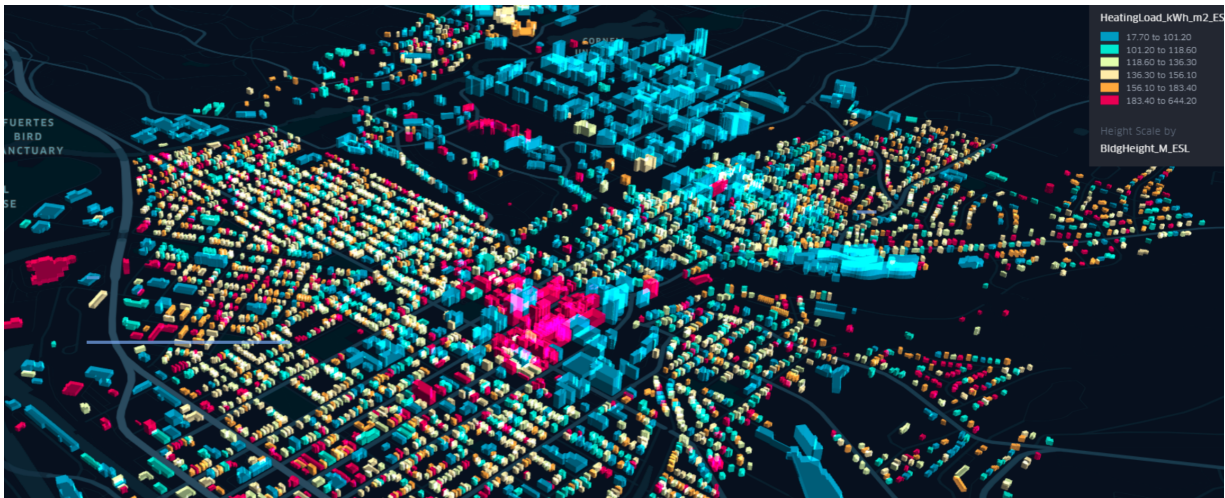


Figure 1: UBEM for Ithaca, NY. Simulation-derived heating energy load visualized in an interactive interface.

available and show actionable planning-related applications that can be used to accelerate urban decarbonization goals using our models when no such data is available. The energy maps serve as an interactive decision-making tool to give city stakeholders an overview of the bigger picture. They also satisfy their need for an in-depth understanding of building energy use to address pressing questions municipal sustainability leadership is facing when implementing decarbonization measures. The presented approach can be scaled to many other jurisdictions and may serve as a uniquely valuable decision-making tool in the context of the Inflation Reduction Act (IRA) and the new federal focus on building decarbonization.

Researchers are working on advancing bottom-up energy simulation methods that can cope with thousands of buildings (Dogan & Reinhart, 2017; Fonseca, 2016; Reinhart et al., 2013) as well as full automation of UBEMs creation (Ang et al., 2022; Dogan et al., 2016; Dogan & Reinhart, 2017; New et al., 2018) and calibration. This allows modelers to use these models to understand the impact of technology adoption scenarios (Bass et al., 2020) at a large scale. However, these UBEM approaches remain difficult to use and require significant domain expertise and computational resources, which are rarely available at the small to medium-sized municipal government level. Hence, BEM support for policy-making and urban decision-making is often only used in the single-building scale (Crawley, 2019), if at all, to define codes and standards for new construction. This paper proposes an automated workflow to fuse Lidar, tax assessment, building permits, and municipal building records with DOE Reference, Prototype Building templates, and utility data to create comprehensive UBEMs to provide municipalities with actionable information that can be leveraged for the decarbonization of the building stock. The methodology is unique as it fully integrates data pre-processing of typical US data sources, simulation engines, and optimization algorithms that allow automation of model creation and calibration.

Methodology

Input Data Pre-Processing Workflow

To create an UBEM (Figure 1), a range of input data from different sources is required and must be interpreted, regularized, and fused. We divide the workflow to process these different model inputs thematically into geometric reconstruction, energy model template extraction, municipal data interpretation, and obtaining baseline model validation data. Table 1 describes all datasets used in this study.

Table 1 Data Requirements for Auto-UBEM

Dataset and Use	Source
Building Footprints (Polygons)	OSM, Microsoft
LIDAR Point Cloud Data (Classified Point Clouds)	USGS, County
Tax Assessment Data (Building use)	City, County
Reference and Prototype Building IDF's (Energy model templates)	DOE
Energy use data (billed or metered) (Validation data)	Utility/Avangrid
Historic Weather Data (Validation)	NREL (PSM3)
TMYx Weather Data (Scenarios)	OneBuilding.org

Building and Shading Geometry

Building footprint data and aerial Lidar (Light Detection and Ranging) data are available nationally. Lidar scans result in 3D point clouds with return information. We classified these into ground, building, and vegetation returns using Esri's ArcGISPro rule-based classification techniques. We then compute the average building height from the building returns and then extrude the building footprint to obtain LOD1 building geometry. In high-density neighborhoods, this provides a sufficiently accurate estimate of the building envelope area for energy simulations. In this study, however, most buildings have pitched roofs, which can lead to unknown errors in photovoltaic yield and envelope heat loss predictions. We implement a custom mesh draping method that discretizes the building footprint in small quads, and their vertices are then snapped to the building return point cloud. This approximates the building roof shape and allows us to create a closed volume by capping the sides with vertical walls stretching from the footprint to the roof edge (See Figure 2). We also tested the elegant Polyfit (Nan & Wonka, 2017) reconstruction approach but unfortunately did not achieve satisfactory results with the Lidar data that was available to us. For select buildings, a photogrammetry and computer vision methodology called FaçadeScanner was used to augment building geometry (Su et al., 2023). We further incorporate contextual geometry, including terrain, neighboring buildings, and vegetation, as shading geometry for radiation mapping analysis. This geometry is reconstructed from the classified Lidar data. Ground return points are used to generate a digital terrain model (DTM) mesh. Vegetation return points are "thickened" by attaching a low polygon cube to each point for ray tracing.

Handling Building Adjacency

Building adjacencies such as the row-house case must be handled to estimate heat transfer surfaces accurately. We implement a custom method that discretizes the building footprints into small segments (0.5m) and then performs a proximity test with neighboring polygons.

Segments where both endpoints are closer than a user-defined proximity threshold (0.1m) and the difference in base elevation from the DTM and building height of adjacent polygons are then used to estimate the area of overlap of the party walls. This area is assumed to be adiabatic and is thus subtracted from the building envelope area computed from the draped mesh model.

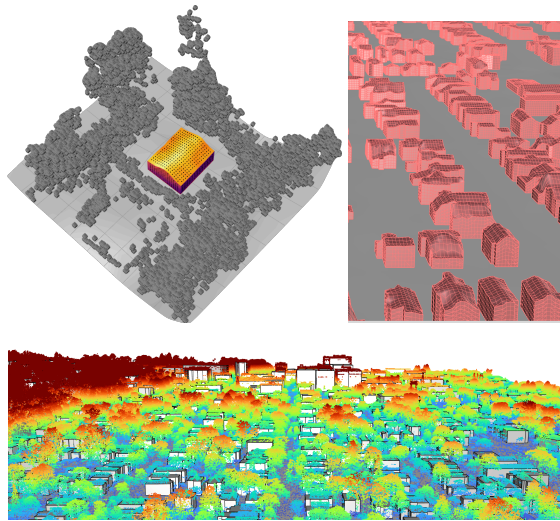


Figure 2: Reconstructed city geometry showing Lidar returns from vegetation and buildings modeled as 2.5D extrusions following the LOD1 definition.

Energy Model Templates

We process DOE Reference and Prototype Building Models for commercial and residential BEM. We extract typical envelope characteristics, systems, installed internal equipment, usage schedules, and occupancy profiles from these models and map the buildings in the modeling domain. To parse and reduce the complexity of the DOE models, we developed a custom routine that is inspired by Archetypal and UMI templates available from UBE.io (Ang et al., 2022) but provides the following improvements: We capture all possible definitions of infiltration objects, parse defined external energy loads such as exterior lighting or elevators and we preserve the multi-zone model definition in the original IDF together with zone area weights so that multi-zone and simplified models can be generated from the extracted data. These definitions are then formatted into JSON files for subsequent utilization in modeling.

Municipal Data:

Tax Assessment Data: At a minimum, building age and building use information is needed from the municipal government. This information is often collected for Property Tax assessment purposes and is thus widely available. The building use classification and age

information is used to map the Energy Model Templates to individual buildings and, together with the building geometry, provide the bare minimum model inputs required to run a simulation (virgin UBE). However, to enhance model accuracy and usefulness, individualizing these templates with additional data is advisable. In this study, additional building information was recorded by the municipality and used to inform the model.

Permit Data: In addition, permit data can be essential to track changes in the building stock and thus can be used to update the virgin UBE. We used regex search commands to regularize and extract information regarding windows, insulation upgrades, heating systems upgrades, and photovoltaic system installations (Figure 3).

Energy Use Data

The local energy utility provided monthly resolution billing system energy use data for gas and electricity New York State Electric & Gas (NYSEG).

Data was anonymized by aggregating billing data for similar buildings. A clustering approach over building characteristics such as floor area, envelope area to volume ratio, building use, age, and construction category was used to identify similar structures. Figure 4 shows monthly averages of the aggregated data.

Building Energy Simulation Model

We implement the 5R1C resistor-capacitor model, a simplified representation of a building zone's thermal behavior as described in the EN ISO 13790 (ISO, 2008). This model is often used for urban building energy modeling (Kämpf & Robinson, 2007) (Fonseca et al., 2016; Prataiviera et al., 2021) due to its simplicity, computational efficiency, and reasonable accuracy (Michalak, 2019). Our implementation is in C# .NET6 and computes ~5000 single zone building models in under two minutes. We extend the original model with EnergyPlus "Simple Glazing" model to improve solar heat gain calculations and simulate systems with fixed efficiencies and COPs, except for air-source and ground-source heat pumps that calculate hourly COPs using the regression fit provided by (Staffell et al., 2012).

Rooftop Solar Potential Simulation

Solar radiation on building rooftops closely follows the methodology introduced by (Jakubiec & Reinhart, 2013) with the following distinctions: Instead of DAYSIM we use the significantly faster ClimateStudio radiation mapping, and instead of a Digital Surface Model (DSM) that drapes over all Lidar points, we separate building roof and façade meshes, ground and vegetation in distinct geometries and thus achieve a more realistic

representation of vegetation geometry. Further, different reflective properties can be applied more easily. We assume ground, facades, and roofs to have 20%, 50%, 20%, and 10% reflectance, respectively. We model vegetation geometry as a 20% reflectance opaque material (Sadeghi & Mistrick, 2022) with the assumption that the partial transparency of the trees (Balakrishnan & Jakubiec, 2016) is adequately modeled due to the fragmented geometry of our trees. One limitation is that we do not model the loss of foliage of deciduous trees and thus underestimate solar potential in the winter season. Dynamic tree materials, as in ClimateStudio, were not available at the time of the study. To estimate the PV yield potential, we assume a panel efficiency of 20% and a coverage ratio of 80%, and only surfaces that receive more than 800kwh/m² or more are included.

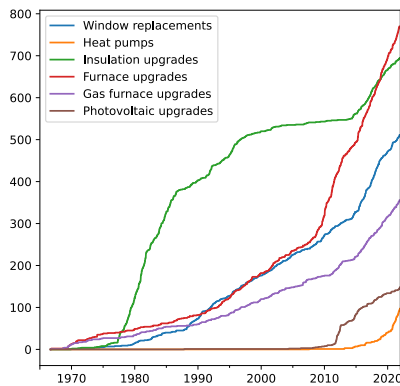


Figure 3: Building permits that recorded envelope or system upgrades are used to close data gaps in city data and to customize building template assumptions for each building in the modeling domain.

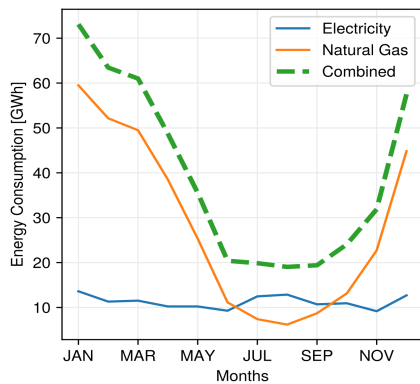


Figure 4: Average annual natural gas and electricity consumption in Ithaca, NY, from 2018-2022.

Model validation and calibration:

Building energy models contain assumptions that introduce uncertainty. Hence, establishing a methodology for validating the generated models is

essential. Guideline 14 (ASHRAE, 2002) describes methods to quantify building energy model accuracy concerning metered energy demand by end-use. Researchers have developed methods to automatically calibrate energy models (Heo et al., 2012; Khanna et al., 2018; Nagpal et al., 2018) to remove or limit uncertainty in the input assumptions. Calibration often requires manual coupling of optimization algorithms and energy modeling tools and cumbersome data exchange via text files written to disk. We directly embed optimization capability in the 5R1C model. When utility data is available, we use the derivative-free, Bound Optimization BY Quadratic Approximation (BOBYQA) (Powell, 2009) numerical optimization algorithm as implemented in CSNumerics. We consider the variables listed in Table 2 as uncertain and thus flexible for adjustment within feasible bounds to fit better simulated and billed energy consumption. The fitness function for the optimizer aggregates billing data into a heating and cooling season to level out billing over billing and billing correction credits due to the estimated nature of this data. The fitness function weights smaller loads, such as heating and cooling season electricity demand and baseline gas demand in the summer, by a factor of two to converge on solutions that best approximate the monthly energy demand shapes.

Table 2 Calibration Variables

Calibration Variables:	Unit:	Bounds:
U-value	W/m ² K	0.1-5
Infiltration rate	ACH	0.1-4
Hot water flow rate	m ³ /h/P	0-0.0001
Equipment power density	W/m ²	0-40
Lighting power density	W/m ²	0-20
Elevator	W/m ²	0-20
External Lighting	W/m ²	0-20
People density	P/m ²	0-0.5
Heating set point	C	18-24
Cooling set point	C	26-off

Scenario definition

The intended use of the calibrated model is scenario simulation to assist the local municipality with urgent questions such as where to prioritize the electrification effort and anticipated cost of upgrades so that the municipal government can develop funding opportunities and economies of scale. We applied a "residential conversion", "commercial conversion", and a "fully electrified" adoption scenario. We applied these adoption scenarios after the calibration was completed and simulated them with EPW TMYx weather.

Building Upgrade Measures and Cost Estimates

To estimate thermal load electrification cost, we tap into the NREL Residential Efficiency Measures Database

(Roberts, 2012) and compute the cost associated with removing old gas boilers and furnaces and replacing them with air-source heat pump systems for space and water heating. We propose a cost estimation framework for retrofit measures. We first define the total cost as the removal cost of the before condition plus the installation cost of the after condition. The installation cost is further divided into a fixed cost (\$) and an additional cost to account for different equipment sizes in (\$/KW). The cost data, however, has several limitations. The NREL database, established in 2012, lacks built-in considerations for inflation. This absence of inflation adjustments implies that cost figures within the database remain static and may not accurately reflect the changing economic landscape over time. To rectify this limitation, we calibrated the cost according to the CPI Inflation Calculator created by U.S. Bureau of Labor Statistics. In addition, financing terms, environmental compliance, and risk factors all play pivotal roles in determining the financial implications that are beyond the scope of this study.

Results

Model Creation: The workflows developed for this study are able to construct the model, including data pre-processing and fusion, as well as simulation of just over 5000 buildings in under 5 minutes on a standard laptop.

Model Calibration: Figure 1 shows a spatial visualization of the baseline UBEModel’s predicted heating energy loads. Figure 6 offers a comparative view of the model’s accuracy with respect to the annual heating demand before and after calibration, compared to the monthly billing records. The natural gas prediction error is noticeably higher than that for electricity. Nonetheless, post-calibration results yield closely aligned distributions for both natural gas and electricity.

Zooming in on specific structures, Figure 7 shows the calibration accuracy of a sample drawn for the modeling domain. The modeled and actual monthly utility demands are in good agreement.

Scenario Simulation: Figure 8 presents the projected load shift from natural gas to electricity for scenario analysis and the resulting carbon emission reduction for the three scenarios evaluated.

Cost Analysis: Figure 9 shows the estimated cost of three thermal load electrification scenarios. The full electrification scenario is estimated to cost \$86M; the residential electrification scenario costs \$55M; the commercial electrification scenario costs \$30M.

Photovoltaic Potential: Figure 10 juxtaposes Ithaca's annual demand for natural gas and electricity against hypothetical PV scenarios of 1300 kWh/m², 1100

kWh/m², and 800 kWh/m². The data suggest that even a

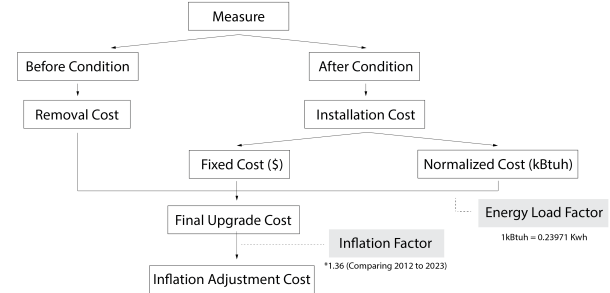


Figure 5: Cost Estimation Framework

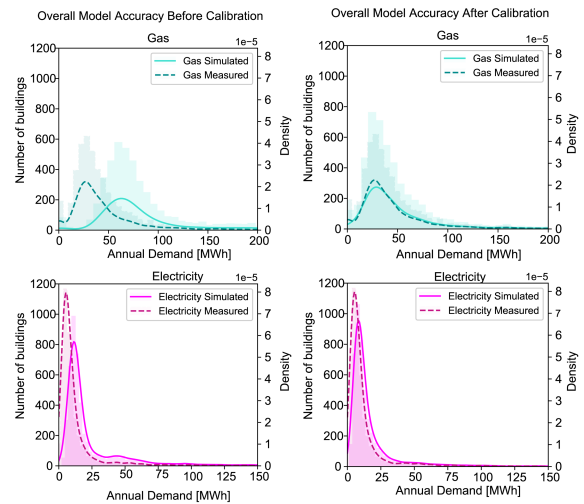


Figure 6: Model accuracy before and after calibration with monthly billing data.

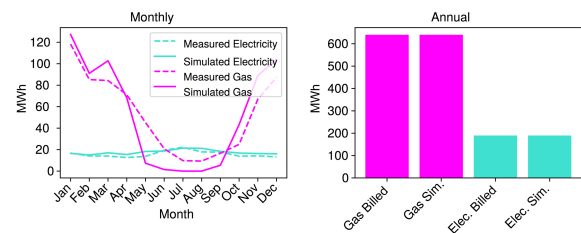


Figure 7: Calibration accuracy for a downtown Ithaca government building

modest PV adoption could satisfy Ithaca's net-zero goal from May to September if all residential buildings are electrified. In the case of commercial electrification, net zero could be achieved from April to mid-September. If all buildings are electrified, net zero could be achieved from the end of March to mid-September.

Discussion

Data outputs lay the foundation for robust planning and timely implementation of decarbonization measures.

The presented workflow demonstrates that automating data processing and model calibration for a small city is feasible. This suggests that UBEMs and their application are scalable by reducing the required effort and complexity to create and use UBEMs. To facilitate data exploration, we developed a web-browser-based data dashboard, as shown in Figure 11. Data can reduce uncertainty around the impact and feasibility of decarbonization measures in buildings by providing various retrofitting solutions in conjunction with their estimated impact on energy consumption for every building. While future work should include more nuanced decarbonization scenarios that test a much broader range of carbon mitigation strategies on the building and energy supply side, the simulated scenarios show that simple conversions of heating and hot water systems to air-source heat pump technology could reduce Ithaca's carbon emissions by up to 78%. This is an encouraging figure and suggests that building stock decarbonization is technically feasible. The integration of financial aspects, particularly through cost analysis of retrofit measures, acknowledges the intricate relationship between technical solutions and economic viability. Among the three simulated scenarios, electrifying commercial buildings is the most cost-effective. Commercial buildings, despite being fewer in number compared to residential buildings, contribute significantly more to the overall thermal load and carbon emissions. Larger floor areas, higher occupancy densities, and specialized equipment lead to amplified heating, cooling, and lighting energy consumption. This suggests that the city's policy efforts should first focus on commercial decarbonization while developing a strategy for residential retrofitting that could potentially bring retrofitting costs down, such as economies of scale and serial retrofitting. The right balance in policymaking is crucial for achieving sustainable and economically viable decarbonization pathways. One limitation of this study is that the NREL database only includes cost data for residential buildings, and we had to extrapolate cost estimates for commercial buildings. Future work on an updated holistic database for retrofitting cost estimation is needed.

Conclusion

In conclusion, Urban Building Energy Modeling (UBEM) shows promise as a tool for informing urban decarbonization strategies, with additional future upside given that data availability is expected to improve with the digitization of city governance and the continued installation of smart meters. Our findings, in their current state, offer a translatable framework for other cities working toward urban decarbonization. The three decarbonization scenarios provide insights into the

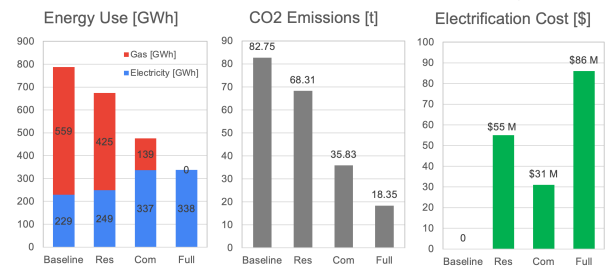


Figure 8: Energy Consumption, CO2 Emission & Cost Comparison of Three Scenarios

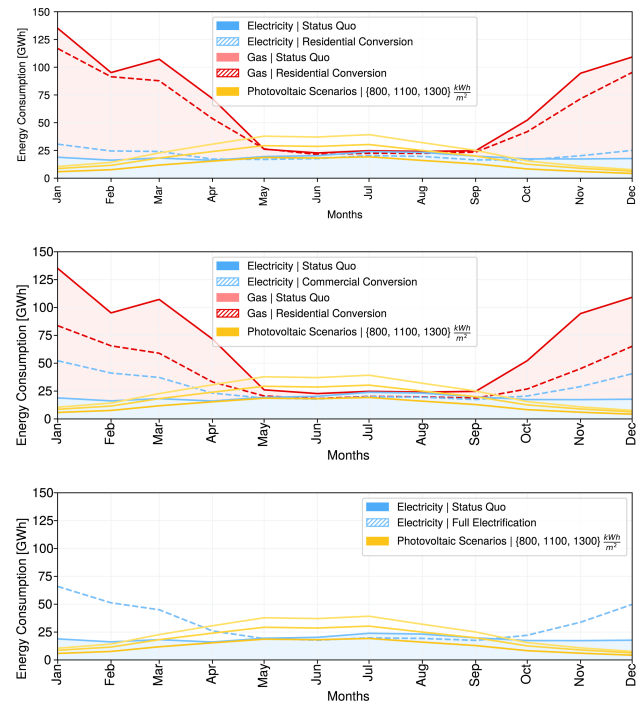


Figure 9: Comparison of Ithaca's annual energy demands against potential PV scenarios of 1300 kWh/m², 1100 kWh/m², and 800 kWh/m², as low, medium, and high, respectively.

anticipated change in utility peak loads. The cost analysis of retrofit measures could assist policymakers in drawing up the city's budget for carbon reduction. The complex relationship between cost and thermal load electrification involves a combination of technological advancements, policy support, market dynamics, and societal considerations. Ultimately, as cities continue their missions toward a sustainable and resilient future, scaling up UBEMs will serve as both a bottom-up and top-down tool for fundraising, local community engagement, and consensus building.

Acknowledgments

The authors would like to thank the Atkinson Center, NYSERDA, and Park Foundation for funding this research. Further, we would like to thank AVANGRID for sharing validation data for this research.

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Figure 10: Solar potential of rooftops in Ithaca.

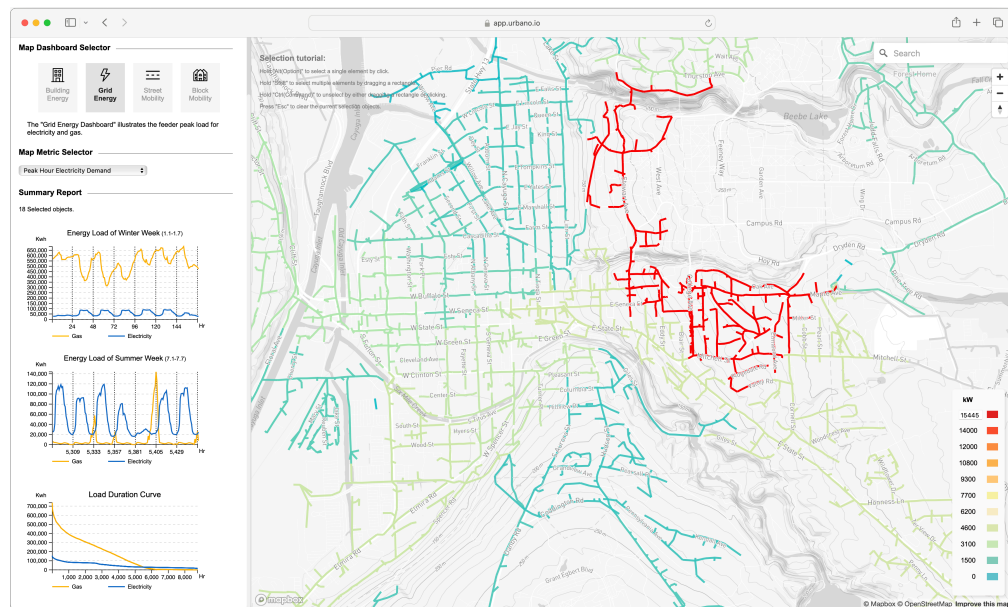


Figure 11: Data dashboard to visualize load in gas and electricity feeder lines in Ithaca.

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