Energy & Buildings 285 (2023) 112861

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enb

Developing and tuning a community scale energy model for a disadvantaged community

Robert Flores [a,*], Sammy Houssainy [b], Weixi Wang [a], Joseph Robertson [b], Khanh Nguyen Cu [b], Ben Polly [b], Ramin Faramarzi [b], Jim Maclay [c], Jack Brouwer [a]

[a] Advanced Power and Energy Program, University of California, Irvine CA 92617, USA
[b] National Renewable Energy Laboratory, Golden, CO 80401, USA
[c] Altura Associates, Newport Beach, CA 92660, USA

ARTICLE INFO

Article history:
Received 23 September 2022
Revised 17 November 2022
Accepted 3 February 2023
Available online 9 February 2023

ABSTRACT

This work describes the development of a community-scale energy model for a mixed-use low-income community located in Huntington Beach, CA. An accurate community-scale energy model is useful for evaluating the use of limited capital resources used to invest in clean energy technologies. This work lays out the process of developing such a model while relying primarily on publicly available data and highlighting critical partnerships necessary for model development success. The primary contribution of this work is the demonstration of the process used to develop an accurate energy model for a disadvantaged community when minimal building and energy use data is available. The heart of the model is the physics-based community scale energy modeling platform URBANopt. Using a bottom-up load modeling approach, energy simulated energy use falls within 3% or less of aggregate annual utility data, and within 10% or less aggregate monthly utility data. The demonstrated model development and tuning process can be used by others to characterize other atypical communities, which may differ significantly from prototypical models.

1. Introduction

The purpose of this paper is to describe the process used in developing and tuning a community-scale energy model in preparation for evaluating the impact of clean building energy technologies and upgrades throughout a disadvantaged community. Community-scale energy modeling (CSEM) is the process of developing energy models for multiple buildings and energy systems located in the same community. This is also known as urban building energy modeling (UBEM) when considering an urban community. The number of buildings captured in these modeling approaches ranges from a single neighborhood with tens of buildings, to entire cities with hundreds of thousands of buildings [1]. A key benefit of CSEM and UBEM is the ability to evaluate the widespread energy, environmental, and economic performance of clean building energy technologies prior to implementation. Since these technologies tend to cost more [2] and have long lifespans [3,4], it is critical to understand technology performance and interactions. This is critical in low-income communities with limited and/or highly constrained capital.

CSEM/UBEM applications have spanned the characterization of energy use for entire cities [5,6],to the design and evaluation of clean energy technologies and building-to-grid technologies across a neighborhood [1]. Aside from characterizing city energy use, CSEMs and UBEMs are typically based on physics-based building energy models (BEM) [7], such as EnergyPlus [8], using paired with standardized BEM templates (e.g., the U.S. Department of Energy Prototype Building Models [9–11]). A general approach relies on automated BEM assembly based on a reduced set of building data (building geometry, vintage, end-use, etc.). [12,13].

The direct application of this approach results in BEM generation for each building captured in a particular design area. For example, the CityBES model described in [14] uses public building records to develop EnergyPlus BEMs for all buildings within a geographical area. This model is demonstrated and used to evaluate five energy conservation measures across 940 office and retail buildings in San Francisco. Another example focused on urban residential building design and placement is presented in [15]. A more data-intensive approach is demonstrated in [16]. This approach relied on custom building urban BEMs tuned using real interior temperature data to examine the effect of building design on interior comfort. Although this work does not follow a traditional automated

* Corresponding author.
E-mail addresses: rjf@apep.uci.edu (R. Flores), Sammy.Houssainy@NREL.gov (S. Houssainy), ww@apep.uci.edu (W. Wang), Joseph.Robertson@nrel.gov (J. Robertson), KhanhNguyen.Cu@nrel.gov (K.N. Cu), Ben.Polly@nrel.gov (B. Polly), Ramin.Faramarzi@nrel.gov (R. Faramarzi), jmaclay@alturaassociates.com (J. Maclay), jb@nfcrc.uci.edu (J. Brouwer).

https://doi.org/10.1016/j.enbuild.2023.112861
0378-7788/

Nomenclature

ACPF (AC)	Alternating current power flow
ACS	American Community Survey
BAHSP	Building America House Simulation Protocols
BEM	Building Energy Model
CBECS	Commercial Building Energy Consumption Survey
CSEM	Community Scale Energy Model
DEER	Database of Energy Efficient Resources
DER	Distributed energy resource
DHW	Domestic hot water
DOE	Department of Energy
EE	Energy efficiency
EUI	Energy use intensity
FFA	Finished floor area
HVAC	Heating, ventilation, and air conditioning
OS-HPXML (HPXML)	Open Studio – Home Performance eXtensible Markup Language
RECS	Residential Energy Consumption Survey
TDV	Time Dependent Valuation
SDK	Software Development Kit
UBEM	Urban Building Energy Model

BEM development workflow, this work captures efforts to examine energy use and occupant comfort in a dense urban setting.

The efforts described above result in the production of BEM for each building in a design area. Although this approach can maintain unique building details, computational effort increases with each building. Statistical and machine learning methods have been applied to reduce computational. One approach uses statistical and machine learning methods to group buildings into "archetypal" building clusters. After grouping, the "archetypal" BEMs are simulated, and results are scaled to buildings within each cluster. This workflow is described in detail by Reinhart et al., [12], and is applied using EnergyPlus to simulate archetypal buildings in [17–20], and by Fonseca et al., which uses a custom BEM approach [21,22]. A different approach machine learning is presented by Nutkiewicz et al. [23,24]. Detailed EnergyPlus models are used to train a neural network. The neural network is then used in place of BEMs to predict energy demand in other buildings.

Current UBEM development relies on detailed building energy data and/or existing buildings matching prototypical BEM models. In many instances, building energy data may be unavailable due to privacy concerns, lack of civic energy disclosure requirements or properties falling below disclosure threshold requirements (e.g., building floor area below reporting threshold), and/or difficulty associated with soliciting building energy data directly from tenants and property owners. Residential energy use surveys report wide variance in how energy is used [3] and efforts to relate usage to socioeconomic, climate, and building factors has proven difficult [25–28], potentially resulting in large differences between a real community and a model based solely on prototype BEMs. This paper focuses on the situation where energy data is only available at the aggregate community level and current prototype BEMs do not capture actual energy use in the community.

The current work adds to the existing literature by demonstrating a process for developing an accurate community scale energy model for an atypical community when detailed energy data is unavailable. This addition develops a roadmap for the development of a community scale model by highlighting datasets, tools, and partnerships that were key to accurate model development. This contribution is accomplished through a case study of the low-income Oak View community, located in Huntington Beach, California. The community energy simulation tool URBANopt [29,30] was used for CSEM development. The current effort is focused on describing the model development process. Subsequent work will analyze the application of clean energy and microgrid across the community. This work also includes the demonstration of a new single-family building energy model workflow designed to simulate the stochastic nature of residential energy use [31], and consideration of the local electric distribution circuits through development of an AC power flow (ACPF) model.

The paper is organized as follows. Section 2 describes the design area (the Oak View community). Section 3 describes the URBANopt and ACPF modeling platforms used in our analysis. Section 4 develops the process for building and tuning the CSEM and ACPF simulation. Section 5 evaluates the CSEM and ACPF simulation results. Section 6 provides a discussion on the extensibility and scalability of the CSEM approach, the accuracy of the model, and pathways towards improving model accuracy.

2. The Oak View community

The Oak View Community is in Huntington Beach, Orange County, California at 33.71°N, 117.995°W, or under 2010 U.S. Census Tract 994.02 [32].. The community population is approximately 8,090 residents. Maps of the Oak View neighborhood are shown in Fig. 1. The current work focuses on a subset of buildings in the community, shown as the Oak View Microgrid Design Area in Fig. 1b.[1] The design area includes 286 residential and 31 commercial, industrial, and educational buildings. The Oak View Community was selected for this work because it qualifies as a disadvantaged community under the California State definition [33]. Factors that contribute to the disadvantaged community designation are [34,35]:

- Household income is 36 % lower than county average
- Per capita income is 51 % lower than county average
- Home ownership rate (≈25 %) is 56 % lower than county average
- Less than 37 % of the population have attended some college or education beyond high school, versus 64 % for Orange County
- The CalEnviroScreen 3.0 environmental burden is in the 83rd percentile for California, driven by local toxic releases proximity of residential buildings to a solid waste transfer and hazardous waste facility seen in Fig. 1b, and the persistent heavy vehicle traffic in the area
- The CalEnviroScreen 3.0 social burden is in the 62nd percentile, driven by low education levels, high housing burden, linguistic isolation, and high poverty rates

Fig. 1 provides additional detail on the location and building types for all buildings.

3. Community-Scale modeling tools

3.1. Community-Scale energy model development

This section describes the URBANopt software [29,37], the stochastic single-family detached BEM workflow (or the OpenStu-

[1] This work is in service of a project examining the potential to convert a low-income community into a microgrid to ensure reliable energy service during adverse events.

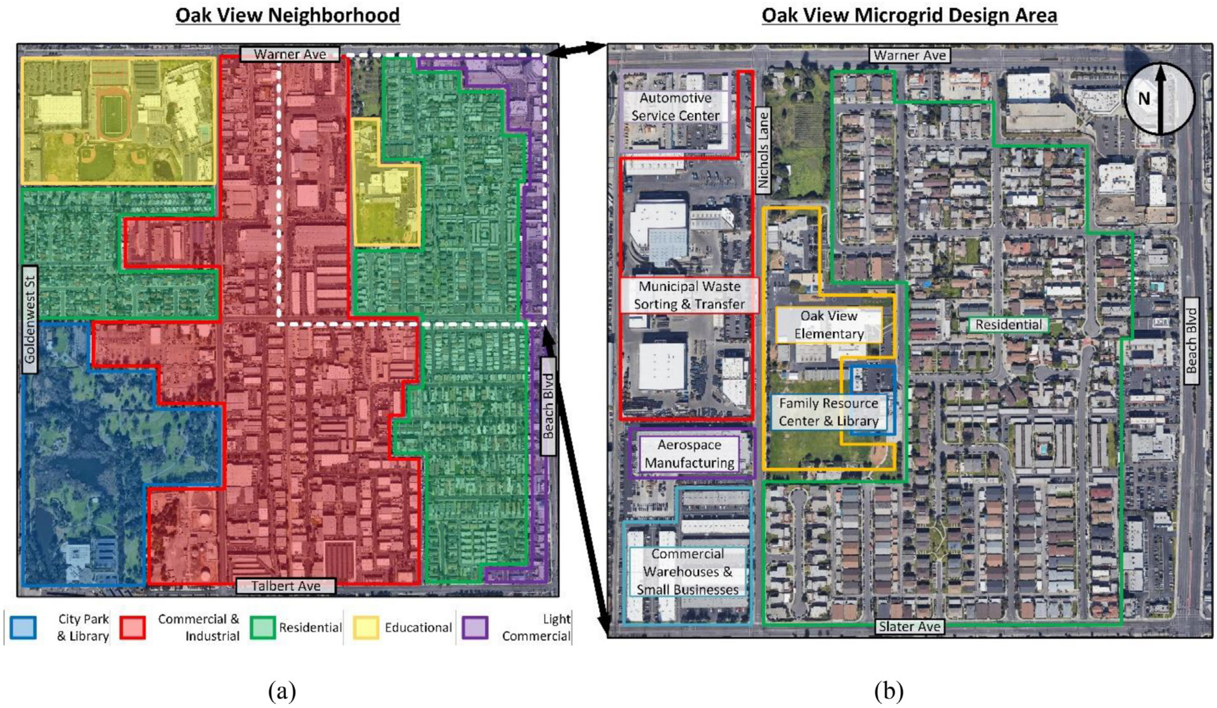

Fig. 1. Aerial images and building cluster information for the Oak View neighborhood, and additional building details for the Oak View Microgrid design area. North runs top to bottom in the image. Aerial images are from [36].

dio Home performance XML - OS-HPXML [38]), and the typical workflow used for all other buildings.

3.1.1. URBANopt software

URBANopt is a physics-based energy modeling platform for districts and communities [29,30]. URBANopt is designed as a modular, open-source SDK, and is built on top of the U.S. Department of Energy (DOE) open-source tools for simulating individual buildings: EnergyPlus, OpenStudio, and Spawn of EnergyPlus. URBANopt includes capabilities and workflows that enable multi-building analysis at a neighborhood, district, or campus scale (generally 10 s to 100 s of buildings), and connections to other tools and engines that allow for the analysis of shared energy systems, distributed energy resources (DER), and the electric distribution systems, including interactions and impacts with building efficiency and demand flexibility strategies [39].

URBANopt helps manage geospatial information for modeling a community and automates the creation of detailed physics-based models for baseline scenarios (e.g., existing conditions) and advanced performance scenarios (e.g., retrofit upgrades). URBANopt manages and automates data exchange with other tools or engines, manages simulations, and aggregates/post-processes results for evaluation and comparison of scenarios. In total, the Oak View community-scale model is captured in one GeoJSON file that describes building geometry, energy systems, and building end use, one CSV file used to tune and implement different scenarios, and a separate CSV file linking building models to scenarios. While URBANopt workflows for generating commercial building models have been described elsewhere [29,40], this paper describes in detail newer URBANopt workflows for generating models of low-rise single-family detached residential buildings, which were used in the Oak View energy model, and the general workflow used for all other building types.

3.1.2. Single-family detached OS-HPXML building models

Models for residential buildings were created using the OS-HPXML workflow. The general workflow is depicted in the flow chart shown in Fig. 2. This flow chart depicts the process of assembling URBANopt input files combined with BEM assumptions to generate descriptions of individual dwelling units that are merged to form a single BEM. One major difference between the OS-HPXML and other OpenStudio workflows is the direct manipulation of residential building energy systems, including common appliances, residential space conditioning, and hot water systems. In general, the workflow operates using Home Performance XML (HPXML) building description files and consists of applying several OpenStudio measures that build residential EnergyPlus models. Each EnergyPlus model represents an individual residential dwelling unit: a single-family detached building, or a single unit of a single-family attached or low-rise multifamily building. In this case, only single-family detached buildings were modeled using the OS-HPXML workflow.

URBANopt uses the following OpenStudio measures of the OS-HPXML workflow:

- BuildResidentialHPXML: this measure builds an HPXML file based upon a set of building description inputs. Feature information contained in the URBANopt GeoJSON file, along with default assumptions contained in both lookup files and ANSI/RESNET/ICC 301–2019 [41], are used to populate its arguments.
- HPXMLtoOpenStudio: this measure translates the HPXML file to an OpenStudio model.

These measures are called sequentially by the BuildResidentialModel measure, developed for URBANopt, for each dwelling unit in a single-family detached/attached (e.g., see Fig. 3) and low-rise multifamily building feature contained in the URBANopt GeoJSON file. Individual OpenStudio models corresponding to multiple dwelling units of a building are merged into a single OpenStudio model. For more information on how single-family detached, single-family attached, and low-rise multifamily buildings can be modeled using the single unit -based approach, see the Residential Workflows [42] section in the URBANopt SDK Documentation.

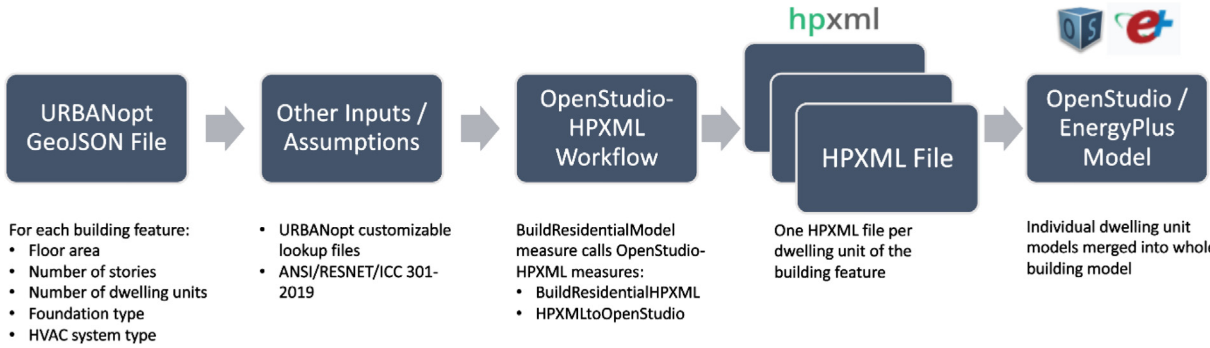

Fig. 2. Flowchart depicting the process of converting URBANopt GeoJSON files into a complete BEM. Each individual HPXML file describes single dwelling units, which are then assembled to form a BEM. For the current work, only single-family detached buildings are modeled using this workflow.

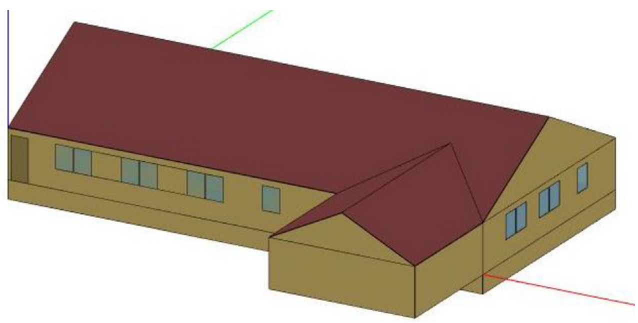

Fig. 3. 3D rendering of example residential single-family detached building energy model. Image is taken from [43].

A separate GeoJSON schema was developed specifically for building types supported by the OS-HPXML workflow. The schema makes certain high-level inputs available for easy adjustment by URBANopt users, while other inputs can be adjusted using lookup files (as noted above). Current high-level inputs consist of required fields such as floor area, number of stories, and foundation type, as well as optional fields such as heating ventilation and air conditioning (HVAC) system type and presence of an attached garage. Additionally, occupant-related schedules can either be defaulted according to the 2010 Building America House Simulation Protocols (BAHSP) [44], or stochastically generated using time-inhomogeneous Markov chains derived from American Time Use Survey data [31]. Schedules are currently defaulted to be stochastically generated but can be modified using the BuildResidentialModel measure.

3.1.3. DEER building models

The origin and history of Database of Energy Efficient Resources (DEER) building energy models are described within the context of matching BEM templates to real buildings in Section 4.1. In general, DEER BEMs and associated workflows are like existing U.S. DOE Prototype Energy Models. However, construction sets are based on California building construction requirements.

3.1.4. URBANopt model parameters

Prior work has shown that EnergyPlus models contain more than 3,000 tunable parameters, 150 of which have a measurable impact on BEM accuracy [45]. Due to the scale of the current project and limited building information, a major goal of the model was to reduce model inputs to match with public data and information collected from local governments while maintaining model accuracy. Additionally, it was important to allow for the tuning of individual BEMs to enable the ground-up load construction approach described in Section 4.

In total, the current approach uses 14 BEM inputs, including building geometry, end use, vintage, space conditioning and DHW system definitions, thermostat settings, and energy load scalars (e.g., parameters to increase or decrease end use loads like lighting, plug loads, DHW, etc.). BEMs developed using the OS-HPXML included additional energy load scalars associated with individual large appliances and loads.

3.2. Energy infrastructure model development

Energy infrastructure models only capture systems operating inside the design area highlighted in Fig. 1. Energy surveys and community interviews showed that nearly all energy delivered to the community was either electricity or natural gas. The purpose of an energy infrastructure model in this work is to understand how local energy infrastructure will react to the introduction of clean building energy technologies. Since many of these measures will reduce natural gas, a model of the gas distribution system is not necessary. DER and electrification measures, however, could lead to phase imbalances, voltage deviations, and over-ampacity issues across the electric distribution system. As a result, the electrical distribution system is the primary focus of energy infrastructure model development.

The electric distribution model was developed using the alternating current (AC) power flow simulator OpenDSS [46]. The OpenDSS tool can fully resolve a three-phase distribution system, including both cables and transformers. There are ongoing efforts to incorporate an OpenDSS module into the URBANopt SDK [47]. These efforts will allow for direct integration between the community scale energy and electrical infrastructure models.

A description of how the OpenDSS circuit model was developed is presented in Section 4.5. Two important factors relevant to model development are system voltage and ampacity constraints. For voltage, the National Electrical Code requires voltage to be within ±5 % of nominal voltages [48,49]. For ampacity, current through electrical components (e.g., cables and transformers) can be limited by joule heating [50]. Both anecdotal evidence and documented system performance metrics indicate that the current electrical distribution systems operates both consistently and reliably [51]. As a result, initial model development is focused on sizing components to replicate stable operation within the ACPF model.

4. Community-scale energy model development

This section describes the process used to develop Oak View CSEM with an emphasis on critical datasets and resources. The goal of model development is to produce an accurate and physics-based representation of how energy is used in the community. The first

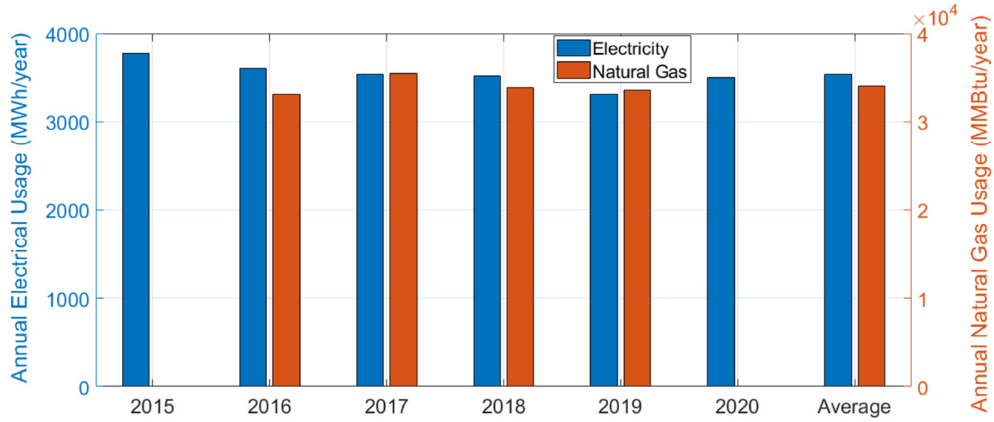

Fig. 4. Annual electric and natural gas demand in the residential sector highlighted in the Oak View Microgrid design area (2015 and 2020 gas usage data was not provided). Average electricity and natural gas use across all residential buildings is 3540 MWh and 33,780 MMBtu per year, respectively.

critical dataset is actual utility usage data for the community. Local electrical and natural gas utilities provided aggregated energy use data for all residential customers in the Oak View design area. The annual residential usage is shown in Fig. 4 (2015 and 2020 gas usage data was not provided). This data shows that, on average, the residential customers in Oak View use 3540 MWh of electricity and 33,870 MMBtu of natural gas per year. Aggregate commercial and industrial usage data was not available due to privacy concerns.

The general process for assembling the community-scale energy model consisted of six steps. First, building geometry, construction sets, and energy systems were defined in a GeoJSON format and used as inputs to the URBANopt modeling platform.[2] Second, building energy systems were defined using OpenStudio measures. Examples include HVAC and water heating system types and efficiencies. Third, baseline predictions for building energy end uses were developed using a combination of building energy surveys and accepted modeling guides [3,4,52,53]. Fourth, individual BEM end use energy loads were adjusted to match baseline energy predictions developed in step 3. Fifth, aggregated BEM energy loads were compared against both the utility data shown in Fig. 4, and energy use survey data [3,4,53]. Major sources of error were identified, resulting in the final adjustment to the community-scale model. This workflow is presented graphically in Fig. 5, which also indicates data sources and inputs. Finally, energy simulation results were then fed into an ACPF model and electrical distribution component sizes were adjusted to accommodate voltage and ampacity requirements.

The different types of data used to develop the tuned community-scale energy model presented in this work can be broken down into four categories:

1) **Building structure**: The geometry and materials used to construct the opaque building envelope, fenestration, and interior walls and features.
2) **Building energy systems**: The performance characteristics of end use energy systems, such as HVAC, domestic hot water (DHW), appliance, lighting, and all other devices/systems/appliances powered by electricity or natural gas.[3]
3) **Disaggregated building energy use**: Patterns that define how and when energy is used in a building.
4) **ACPF tuning**: Sizing and adjustment of electrical distribution system components to enable safe and reliable operation

All data sources used in this work are publicly available or can be acquired through partnerships with local governments and agencies (e.g., public record information and/or anonymous utility data).

4.1. Building structure

State and Federal agencies have both developed building "prototypes" used in BEM designed to emulate typical buildings [9,54–56]. One set specific to California is the DEER Database [57]. These California building prototypes were originally developed to support of cost-benefit analysis of ex ante energy efficiency (EE) (or incentives used to reduce initial EE investment costs) [58]. This analysis originally used the DOE-2.1 building energy simulation platform, but has been converted for use with OpenStudio [59–61]. Specific DEER construction sets differ between building type, vintage, and relevant California building energy code Title 24 [62]. This work assumes that the Oak View is accurately captured using the DEER prototypes. Building vintage was based on tax lot data provided by the City of Huntington Beach coupled with site visits and occupant interviews.

Building geometries were developed using aerial images [63,64] and site visits. Geometries were described in a GeoJSON format [65]. Building stories were determined using aerial images and site visits. During geometry development, two assumptions were made for mixed-use and building with asymmetric floor areas across different stories. First, the current residential multifamily building workflow did not account for mixed use buildings (e.g., a residential building with an enclosed garage). In these instances, enclosed garage areas were removed from the building geometry to avoid exaggerating building thermal loads. For buildings with asymmetric floor area by story, these buildings were either modeled as a single-family building when the second floor consisted of a single residential unit over a garage area (e.g., residences along Oak and Emerald Lanes), or the building was modeled as having symmetric floor areas (e.g., residences along Fir Drive and Oak Lane also). Building geometries, DEER BEM templates, and building stores used to model the Oak View community are shown in Fig. 6.

The DEER prototypes also include occupancy and energy intensity assumptions for various types of buildings. These assumptions

[2] Direct use of the community scale model after developing building geometry, construction sets, and energy systems produced annual electricity and gas use estimates 100% higher and 60% lower than actual usage. This result showed the lack of fit between the prototype BEM workflows and actual Oak View energy use.

[3] Building energy system technical performance is not necessary to predict energy use in a community. This information, however, is necessary to predict the impact of energy efficiency measures, including higher efficiency energy systems.

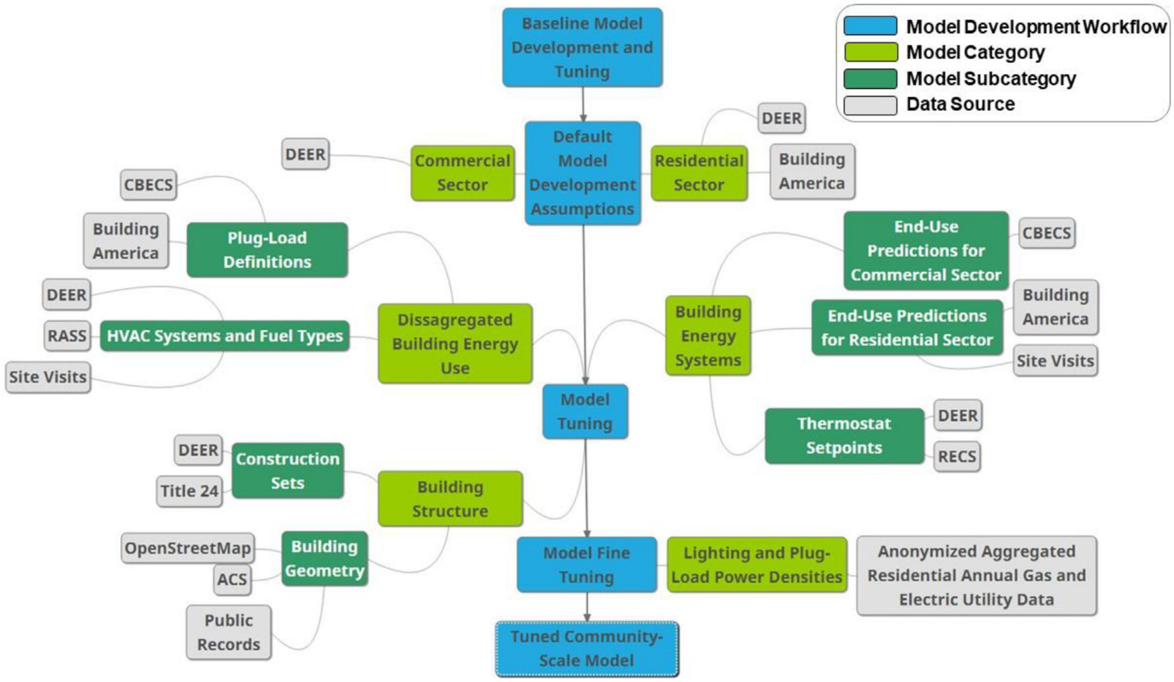

Fig. 5. Summary of model development and tuning process, including data sources used to develop simulation result targets. Aside from the anonymized, aggregated residential load data, community scale and individual BEMs are tuned using a combination of energy survey data, BEM standards (i.e., Building America), and building construction assumptions.

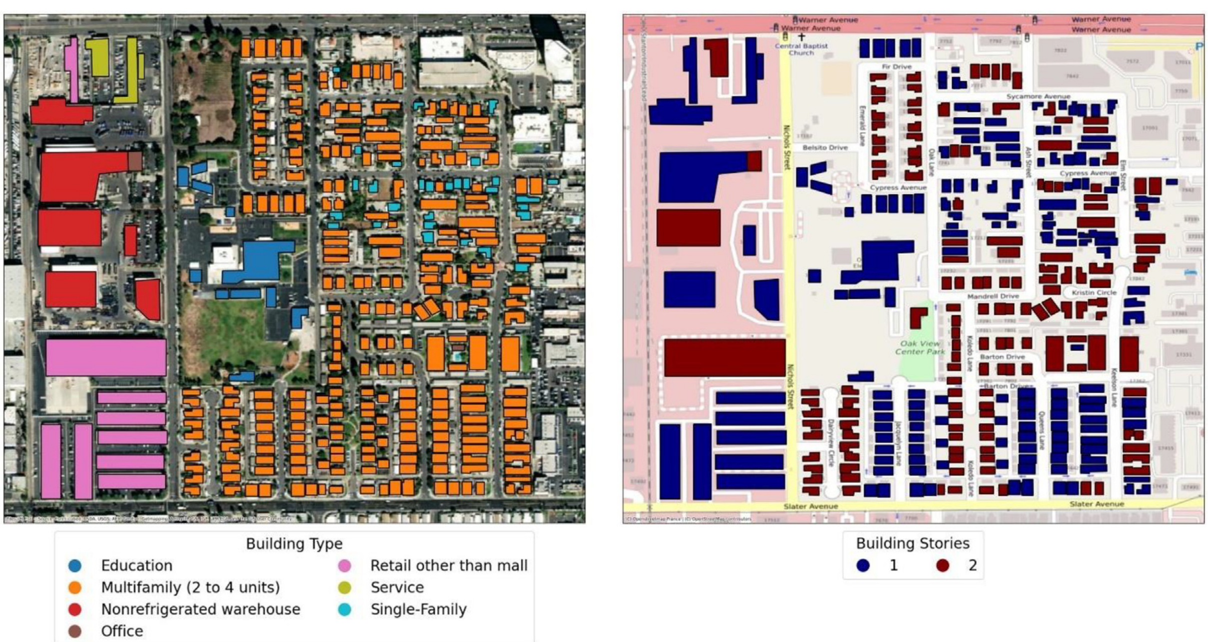

Fig. 6. Building geometries, DEER BEM templates, and building stories for all buildings included in the Oak View Microgrid design area.

were found to be inaccurate at the individual building and community scale when compared to energy survey data [3,4,53], energy prediction models [52], and real utility data. As a result, BEMs were tuned to improve community level accuracy. The tuning process used ‘‘Building America” load predictions and energy use surveys. These load predictions required four inputs: number of residential units per residential building. finished floor area (FFA), garage area, number of bedrooms, and:

- The number of residential units per multifamily building was determined using tax lot and address data provided by the City of Huntington Beach.
- FFA values were extracted from the GeoJSON geometry. Garage area was estimated by counting all enclosed parking spots across the community, followed by assuming that each spot has an area of 20 feet by 10 feet. Garage area was then backed out of FFA. When possible, FFA was compared against public

records, i.e., Redfin [66]. The average residential unit in Oak View has a FFA of 1,240 ft^2.
- The number of bedrooms was based on public records (i.e., Redfin). When unavailable, number of bedrooms were estimated using housing statistics from the American Community Survey [35]. This data source estimates, on average, two bedrooms per residential unit.

4.2. Building energy systems

Building energy systems address the properties of space conditioning and domestic hot water (DHW) systems.

4.2.1. Building energy systems used in Oak View

Building energy system information was collected through site visits and owner/tenant interviews tenants. Commercial and industrial building system information was gathered through contact with property owners and tenants. These interactions also provided details on existing plug and process loads. However, due to a combination of factors,[4] developing accurate commercial and industrial BEMs proved to be difficult. In place, prototypical commercial building DEER BEM templates were used.

Due to the large number of residential buildings in Oak View, less than 20 % of all residential units were visited. These visits revealed that most residential buildings are equipped with all gas appliances. Most buildings lack central air conditioning systems, use wall mounted gas heaters, and have conventional gas tank water heaters. Discussions with property owners, community leaders, examination of utility data, and appliance adoption surveys [53] led to the assumption that nearly all residential buildings mirror the subset of residential units. Each residential unit is also modeled as having a single refrigerator, microwave, two televisions, a dishwasher, and other miscellaneous plug loads. Site visits also showed that most residential buildings have shared laundry facilities.

Two exceptions to these assumptions were a set of buildings that were determined to be fully electrified, and a separate set of buildings that have central air conditioning systems. The set of electrified buildings consists of five apartment buildings with 11 % of all residential units in the community. These buildings all have electric appliances and electric resistive space and tank water heating systems.

Buildings with central air conditioners were easily spotted through the presence of condenser coils outside six residential buildings. It was assumed that these buildings have a central air conditioner and furnace to provide space cooling and heating to the building. Free standing and window mounted single room air conditioning units were observed throughout the community. However, these units were excluded from the current model because an accurate count of total units was unavailable. HVAC systems at each building in the design area are shown in Fig. 7.

4.2.2. Building energy system performance characteristics

The building energy systems modeled include HVAC, DHW, lighting, gas and electric appliances, and all other plug loads. HVAC and DHW system properties were explicitly modeled in OpenStudio. Component properties were based on DEER standards and the relevant Title 24 building efficiency standards. These assumptions are listed in the Appendix:

Appliance, plug load, and process load system characteristics are not explicitly captured in the current DEER modeling workflow. As discussed in the prior section, commercial and industrial plug and process loads were difficult to capture and present in this work. In this case, it was assumed that these loads could be captured using the plug and process load definitions present in the DEER standard, combined with load tuning based on commercial building energy survey results discussed in detail in Section 4.4.

Technical performance characteristics were required, however, to define disaggregated residential energy end uses. In this instance, performance parameters described in [52] were adopted for the current work. This reference contains a series of equations that convert technical characteristics and building characteristics into annual disaggregated energy end use. Relevant appliance performance characteristics adopted for the current work are as follows:

- CFL lighting is assumed to be ubiquitous and operates at 55 lm per watt
- Gas and electric cooktops are assumed to be 74 % and 40 % efficient, respectively
- Gas and electric ovens are assumed to be 11 % and 5.8 % efficient, respectively
- Electric and gas clothes dryers are assumed to process 2.95- and 2.4-pounds damp laundry per kWh energy input, respectively

4.3. Disaggregated building energy use and baseline load development

The method for baseline load development depended on building type. Commercial and industrial buildings were tuned using filtered results from the DOE Commercial Building Energy Consumption Survey (CBECS) data set [4]. Additional tuning efforts were limited due to wide variation in energy use across nonresidential buildings with similar use, and dynamics of business cycles observed within the Oak View community. Details on how the CBECS data was filtered and the resulting end-use load targets are described in the Appendix .

Conversely, there are more high-quality residential energy data sources and end-use load predictions. The NREL Building America Simulation Protocols [52] were used to develop initial load predictions. These equations were exercised using the building parameters described in Section 4.1. Beyond FFA and number of bedrooms, residential unit occupants were based on U.S. Census Bureau American Community Survey (ACS) estimate [67] of approximately-four people per unit.

4.4. Baseline tuning

The data sets described in Sections 4.1 and 4.2 were converted to a GeoJSON format used by URBANopt. OpenStudio electric plug load and gas appliance measures were applied to tune URBANopt simulation results to match with the baseline load described in Section 4.3. Tuning occurred in two steps. First, HVAC loads were tuned to match energy survey data [3,4] through adjustment of model thermostat values. TMY3 weather data files for the Long Beach Airport, located in Long Beach, CA [68] were used in this work.

After thermostat tuning, the complete community scale energy model was benchmarked against measured utility data shown in Fig. 4. Since commercial and industrial building utility data was not available, nonresidential building tuning was resolved once BEM matched DOE CBECS data. Residential energy use buildings were benchmarked against the average annual utility demand data shown in Fig. 4.After tuning residential BEMs to the NREL Building America calculations, residential electricity end use was projected to be 5442 MWh per year (54 % higher than actual usage of 3540 MWh per year). The following adjustments were made based upon an energy audit and the site visits:

[4] Issues and challenges included privacy concerns, limited operational detail, or major changes in equipment and building usage over the course of this work due to external economic and business factors.

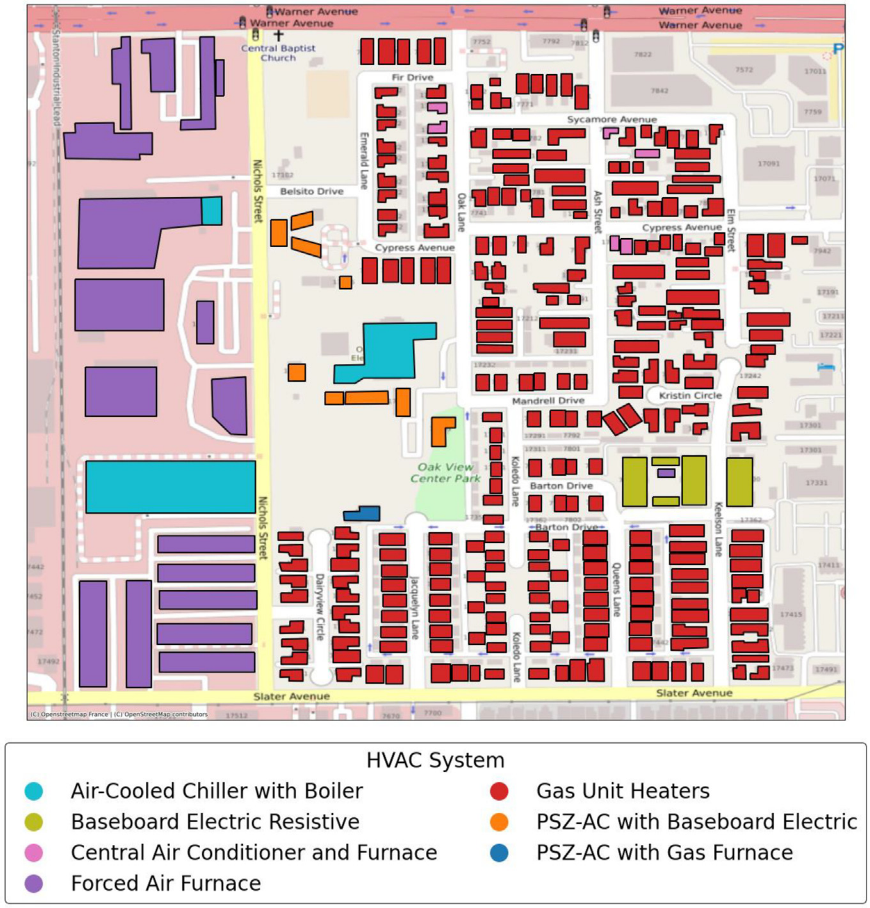

Fig. 7. Building HVAC systems captured in the Oak View community energy use model.

- During site visits, it was observed that numerous tenants do not use all available lighting fixtures. For example, a multi-bulb fixture with a single light bulb. This behavior was not consistently observed across different residential units. Regardless, total interior lighting was reduced by 20 % in each building to account for lower than predicted lighting intensity. This reduced annual electricity uses by 118 MWh per year.
- It was also observed that the appliances and devices typically captured in miscellaneous loads are not present in the Oak View community. For example, HVAC fan systems, high end audio/visual equipment, multiple desktop computers, and other office equipment were typically not present in most residences. These plug loads are captured under "miscellaneous plug load equipment." As a result, the miscellaneous plug load equipment Equation *(5)* shown in the Appendix was modified. First, the constant coefficient of 1595 kWh per year was removed. Second, the remaining coefficients were reduced by 15 %. In total, these modifications reduced community wide demand by 1904 MWh per year. These adjustments are justified given that prior energy survey analyses have shown that energy use can be lower than average in low-income areas [53].

The combination of lighting and miscellaneous plug load modifications reduced the difference between the projected and actual average electrical load from 54 % to 3.2 %.

Natural gas use across all residential buildings was projected to be 244,632 therms per year, 28 % lower than the actual average gas use of 337,860 therms per year shown in Fig. 4. Comparing the NREL Building America natural gas loads to DOE RECS data shows that a potential source of error is due to underestimated DHW energy use. The DOE RECS data set suggests that annual gas use for DHW would be 230 therms per year for an average Oak View multifamily residential unit, or 50 % higher than what is predicted using the Building America calculations. Although the DOE RECS data does not provide sufficient data to determine if this gap is due to system performance or underestimated water use, the NREL Building America model can be manipulated to generate better insight into reasons for error. For example, holding demand constant, DHW uniform energy factor must be reduced from 60 % to 36 % to reduce this difference. Holding system efficiency constant at 60 %, hot water demand must be increased by 60 % to eliminate the difference. The most likely explanation for the difference between the projected and actual gas use is a combination of poorly performing DHW systems and underestimated DHW demand. However, it is more likely that underestimated demand creates most of this difference is due to higher than reported occupancy or other unobserved factors. As a result, DHW demand was increased by 60 %. This adjustment increases total residential gas demand to 329,714 therms per year, or 2.4 % lower than actual average annual demand. DHW demand adjustments were also applied to buildings with electric resistive tank water heaters, slightly increasing total electrical demand to 3,526 MWh per year, or within 0.32 % of actual demand.

4.5. Oak View Microgrid electric power flow model

The AC power flow model development occurred in three steps. First, distribution system circuit maps were used to develop a rough outline of powerline locations throughout the Oak View community [48,49,69]. These resources were cross-references with aerial imagery.

Second, site walks were performed to clear up inconsistencies in circuit diagrams, determine transformer locations and capacities, to link buildings to specific transformers, and to assign single phase distribution lines to specific phases in a three-phase circuit originating from the local electrical substation. In instances where cable and electrical equipment were located underground, or where above-ground transformers lacked kVA ratings, cable and transformer ratings were estimated based on number of connected residential units. Cable gauge could not be measured due to safety concerns.

Third, an initial OpenDSS model was developed using the information captured from circuit maps and site walks. This model was exercised using the electrical demand results from the Oak View URBANopt model. During model construction, cable gauges were tuned to avoid over-ampacity issues. Cable ampacity ratings for copper wire were used but could be easily converted to the equivalent aluminum wire gauge. In instances where transformer power limits were exceeded, building – transformer connections were first examined to ensure correct linkages. If overloads continued to occur, transformer ratings were increased to the proper kVA rating. In eight instances, a pole mounted transformer with a known kVA rating was found to be undersized for the load produced from the community-scale energy simulation. After verifying building to transformer connections, eight transformer ratings were increased to appropriate levels regardless of the labeling, with kVA rating increases ranging between 10 % and 100 %. These adjustments were justified due to the relatively high reliability metrics reported for the circuits that provide service to the community – Smeltzer and Standard [51].

The result of this model development process is shown in Fig. 8. Fig. 8 shows the layout of the above and underground electrical service, highlights where single and three phase circuit paths, and the location of pole and pad mounted transformers.

4.6. Microgrid simulation results analysis

Analysis of the community scale energy simulation presented in Section 5 is provided to establish the accuracy and dynamics of the model. Critical information, such as predicted utility bills, will be addressed in subsequent work. The current work is focused on energy use for the baseline model. Aside from electrical energy and natural gas usage data, the time dependent valuation (TDV) of energy use in California [70] is applied to the Oak View model. The TDV metric was developed to understand how the value of electricity, natural gas, and other energy sources and emissions from these sources change throughout the year on an hourly basis. A component of this metric includes primary energy use for the different energy sources, or the quantity of fossil resources required for the delivery of utility electricity and natural gas. The primary energy TDV value of natural gas is constant throughout the year at 1.0166 kBtu per 1.0 kBtu natural gas used onsite (the TDV value of natural gas is higher than the delivered energy due to transmission and distribution losses). The TDV value of electricity varies depending on time of day and across seasons. This metric is summarized for the quarters of the year in Fig. 9. This figure shows the average hourly TDV primary energy required to deliver 1.0 kWh of electricity. TDV energy trends with solar potential – TDV energy is lowest during daytime, and the spring quarter has the lowest overall TDV energy value due to the high levels of renewable electricity production.

5. Community scale model simulation results

Results from the community scale energy model are presented in three sections. The first section evaluates simulation accuracy and compares simulation results to CBECS and RECS energy use intensities (EUI). Additionally, the residential portion of the URBA-

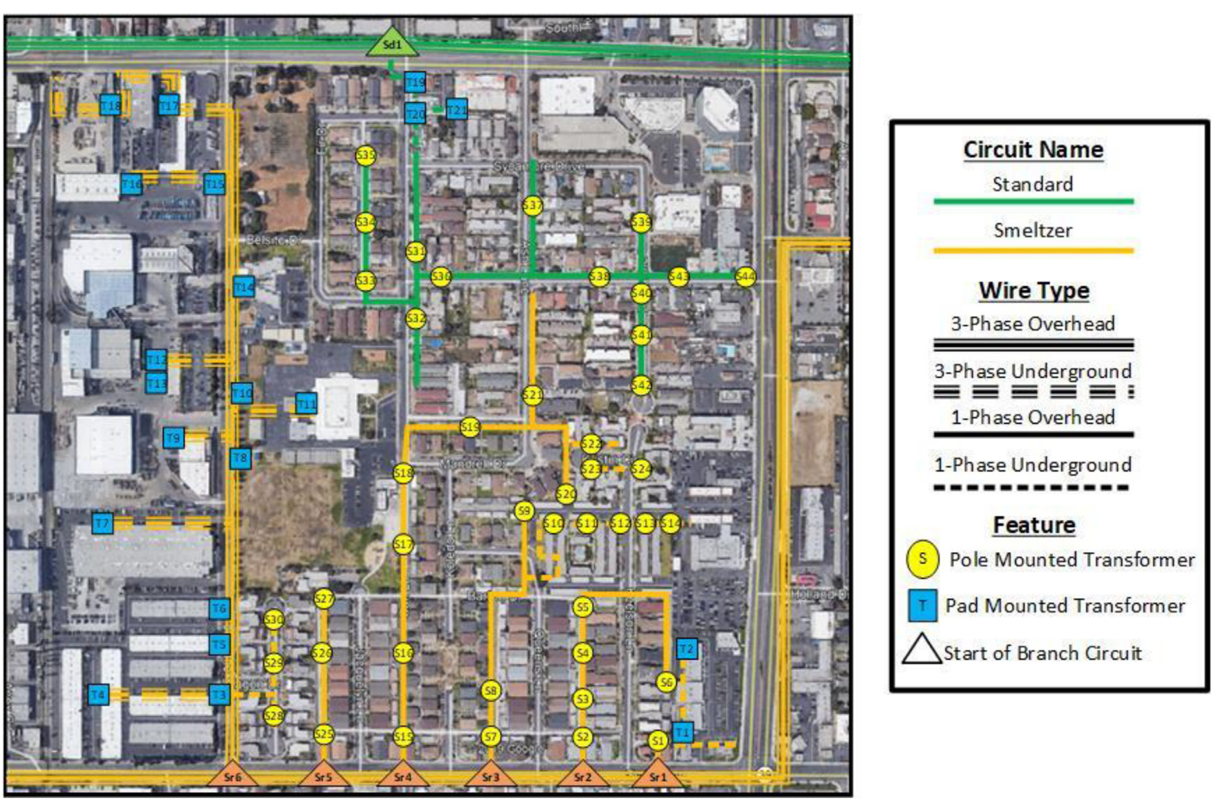

Fig. 8. Circuit map developed to capture the electric distribution system used to provide electricity to the Oak View community. Both the Standard and Smeltzer circuit are powered by the Ocean View substation (not pictured but located to the east of the community) and power approximately 3,000 utility customers each. Oak View customers fed by Standard and Smeltzer combine for approximately 1,100 total customers.

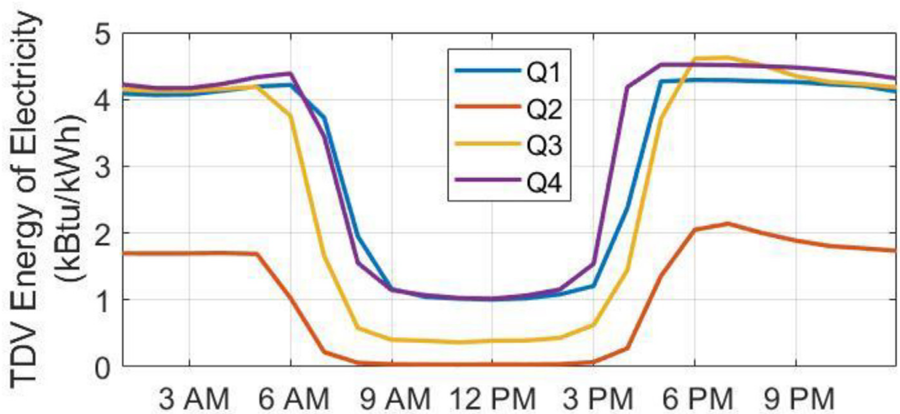

Fig. 9. Average primary energy intensity for grid electricity in California, according to the TDV of energy [70]. Results are presented based on quarterly average across the calendar year. The lowest energy intensity occurs during Q2, or from April to June, and the highest occurs during Q1 and Q4, or October through March. These results are related to renewable resource availability.

Table 1
Modeled annual electric energy use intensity for all major building groups captured in the Oak View community scale energy model. EUI values are provided for every major end use in all buildings and are presented as total electricity use divided by building floorspace. Values are omitted when a building type lacks the specific electrical load (e.g., electric heating, which only exists in a handful of educational and residential buildings).

EUI (kWh/ft^2/year)	Education	Service	Office	Commercial & Manufacturing	Waste Transfer	Residential
Electric Cooling	2.43	–	2.14	1.31	–	0.03
Electric Heating	0.12	–	–	–	–	0.02
Interior Lighting	1.20	2.70	1.90	2.70	2.70	0.35
Exterior Lighting	0.08	0.08	0.08	0.08	0.08	0.08
Electric Plug Loads	4.44	3.46	4.86	3.46	3.46	1.56
Fans	0.38	0.01	0.24	0.11	0.00	0.02
Pumps	0.21	0.00	0.44	0.25	0.00	0.00
Electric DHW	0.62	–	–	–	–	0.40
Total Electric	**9.48**	**6.25**	**9.66**	**7.91**	**6.25**	**2.45**

Table 2
Modeled annual natural gas energy use intensity for all major building groups captured in the Oak View community scale energy model. EUI values are provided for every major end use in all buildings and are presented as total energy use divided by building floorspace.

EUI	Education	Service	Office	Commercial & Manufacturing	Waste Transfer	Residential
Gas Heating ($kBtu/ft^2$)	0.34	1.36	0.55	0.52	0.74	3.14
Gas DHW ($kBtu/ft^2$)	7.48	5.43	5.46	2.10	0.00	15.61
Gas Equipment ($kBtu/ft^2$)	0.33	0.00	0.00	0.00	0.00	4.02
Total Gas ($kBtu/ft^2$)	**8.15**	**6.80**	**6.01**	**2.62**	**0.74**	**22.77**

Nopt model is aggregated and compared against the actual energy use data shown in Fig. 4. The second section explores the energy used dynamics produced by the simulation. The third section shows the results of the ACPF simulation.

5.1. Simulation accuracy

Simulated annual, cumulative EUI's for all major building are provided in Table 1 and Table 2. Electricity EUIs are shown in Table 1 and are separated by end-use categories. Natural gas EUIs are shown in Table 2, also broken down by end-use. As expected, tuned end-use EUIs match targets derived from CBECS, RECS, and Building America Sources. However, these results also show that the simulated cooling demands in office and educational buildings are higher than CBECs results (1.0 and 1.4 kWh/ft^2/year for office and educational respectively). These differences are likely due to 1) the existence of a cooling thermostat schedule throughout the entire year,[5] and 2) a lack of natural ventilation options in the current BEMs. These two factors result in BEM cooling system operation in winter and spring months, outdoor air is available at or below thermostat settings. Tracking cooling in non-summer months (summer is defined as June through September) shows that cooling EUI's could be reduced by approximately 1 kWh/ft^2/year through natural ventilation.

On an annual basis, the current residential sector in URBANopt matches utility electric and gas data within 3.2 % and 0.32 % respectively. Although anonymous, the utility data is provided by billing period. Billing periods for all gas data lined up with calendar months, allowing for direct comparison of real and simulated data. Electric data does not perfectly line up and require filtering to estimate monthly energy use. Real monthly data is presented versus simulated data in Fig. 10.

These results show general agreement between both electrical and natural gas demand. Modeled monthly electrical use is within 10 % of filtered electrical data except for February and January (approximately an 18 % difference). This larger error could be due incorrect data due to billing period matching issues, unmodeled changes in building energy use patterns, the use of standalone air conditioning equipment not captured in the current model or a combination of all factors.

[5] Cooling thermostat settings were 74°F during normal business hours, and 82°F during all other hours. Heating thermostat settings were 70°F during normal business hours, and 64°F during all other hours.

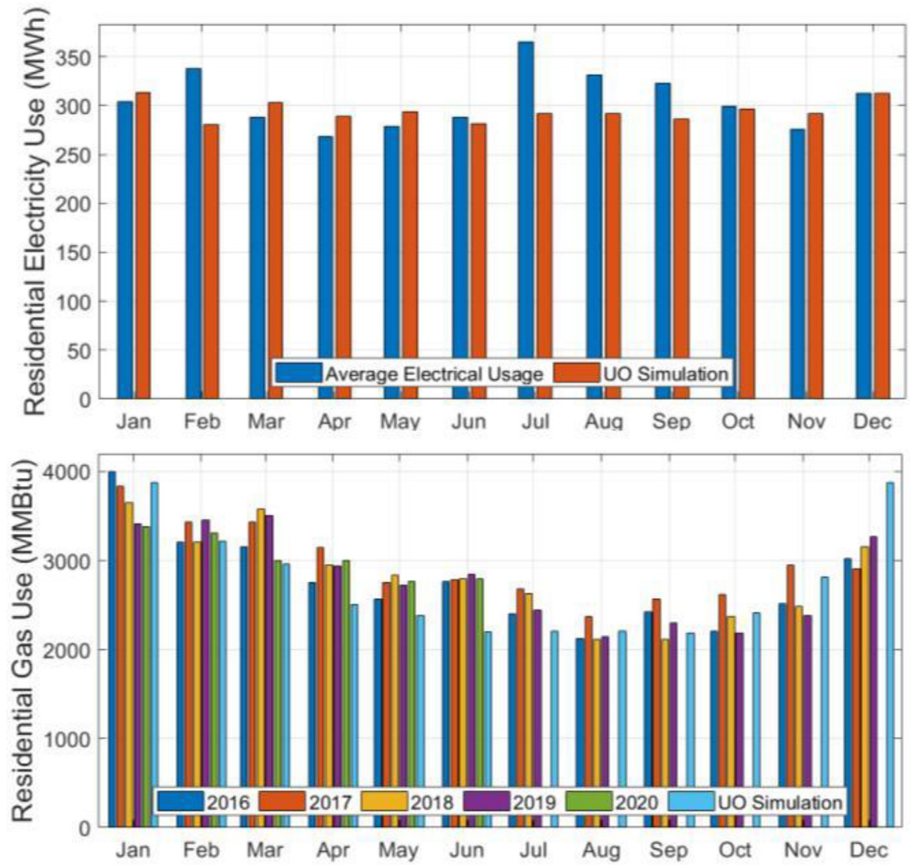

Fig. 10. A comparison of actual monthly residential utility electricity and natural gas use versus simulated use. The actual energy use was provided by local utilities. Electricity results are shown in the top figure, natural gas results are shown in the bottom. Simulated monthly energy use is captured in the plot as "UO Simulation," or URBANopt simulation. Results show good agreement between simulated and actual energy use in the community.

Simulated natural gas use generally tracks actual gas use data throughout the year. Simulated gas use is higher than actual December use and lower than actual spring and summer months. These errors may be due to overestimated space heating paired with underestimated DHW and gas appliance use.

5.2. Simulation characteristics and dynamics

The prior section presented simulated sector wide EUI results and monthly residential sector energy results within the modeled subset of the Oak View community. Additional simulation details on a community and individual building basis are presented in Fig. 11. This figure shows the modeled community-wide energy use per month broken down by building end-use. Corresponding maps show individual BEM EUI. Results are presented for electricity, natural gas, and TDV energy. TDV energy combines both electricity and natural gas on a primary energy basis. Predicted total annual energy use across the entire community is 10.35 GWh electricity, 35,523 MMBtu natural gas, and 56,341 MMBtu TDV energy.

Commercial and industrial buildings account for 66 % of electricity use in the model. Simulation results show that monthly electricity use peaks in summer months, driven in part by increased cooling loads in educational and aerospace manufacturing buildings. Peak use, however, is only slightly above average monthly electric energy use due to a lack of cooling across the residential sector. Examining building electricity EUI results further reinforces the difference in electrical use intensity between residential and nonresidential sectors. However, the highest electric EUI occurs in the fully electrified residential buildings located in the middle east section of community. These high electric EUI results are due to the use of electric resistive systems used for DHW and space heating.

Nearly 93 % of natural gas use is predicted to occur within residential buildings. Gas use in nonresidential buildings is due to a combination of mild winter temperatures, no modeled industrial process loads, and minimal DHW loads. Within each building type, gas use EUI is always higher for 1) single story buildings, and 2) buildings with higher surface to volume ratios (e.g., long thin buildings in the northwest corner). Both results are due to building geometry affecting heat transfer and building energy capacitance.

Electricity and gas results are combined on a primary energy use basis in the TDV energy use plots at the bottom of Fig. 11. On a delivered energy basis, electricity is delivered to the community in nearly equal quantities as natural gas. However, according to TDV energy results, natural gas energy accounts for 64 % of community energy use, or nearly a 2–1 gas to electricity ratio. Combined residential electricity and gas use accounts for 75.5 % of all primary energy use in the community.

In addition to understanding how energy is used in this community, it is also important to understand the dynamics of energy use for a complete analysis of clean energy technologies and impacts on local electric distribution systems. An example week of building hourly electric and natural gas demand dynamics in January are shown in Fig. 12. Figure subgroup a) show the results from a single-family building simulated using the OS-HPXML workflow. All other buildings captured in this figure were simulated using the DEER workflow. Dynamics are shown for both summer and winter months to highlight operational differences in space conditioning systems. Other commercial and industrial buildings are not shown because load shapes for other nonresiden-

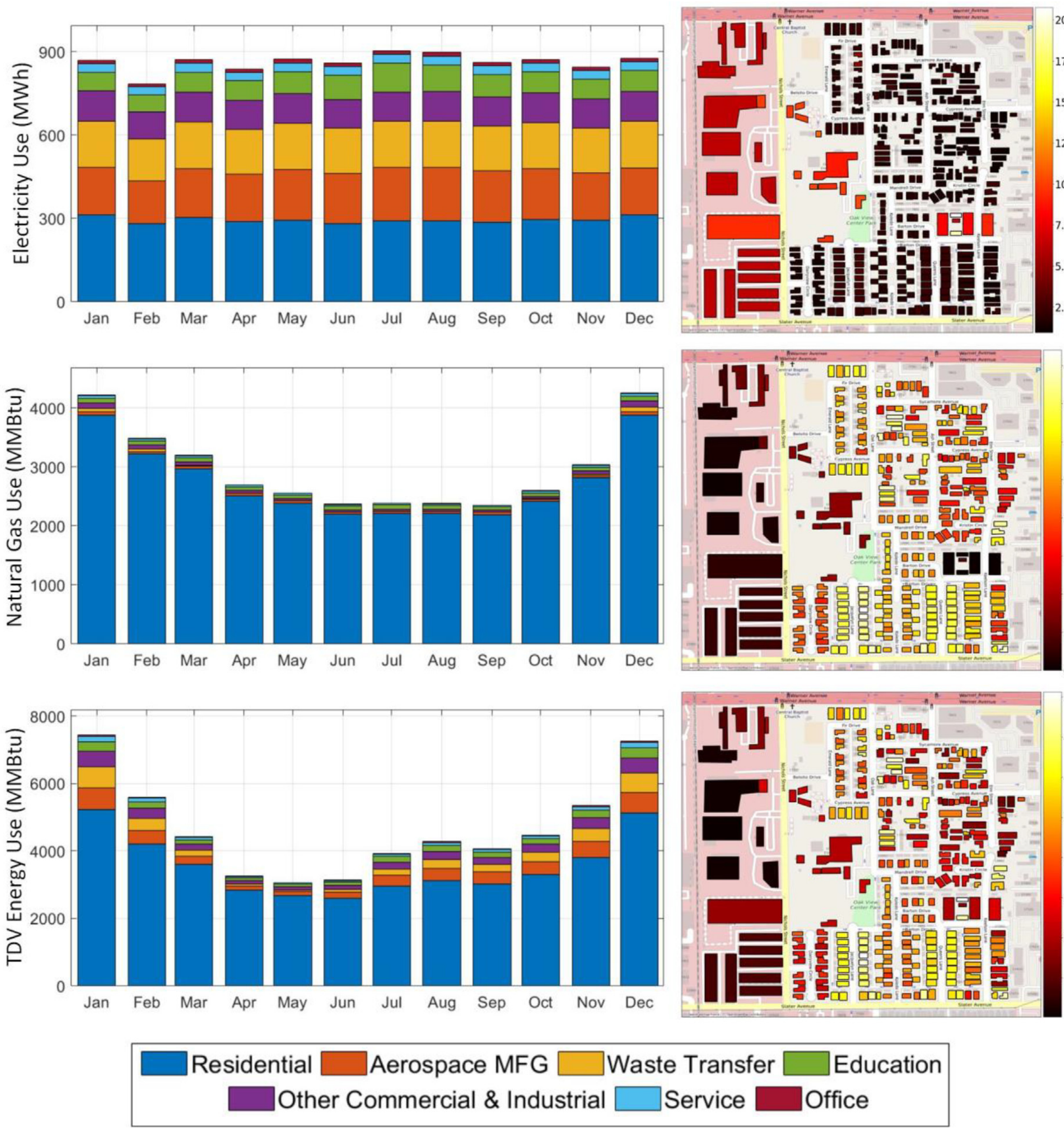

Fig. 11. Modeled community scale energy use broken down by month and building type. Corresponding maps show the modeled annual EUI for each building type, showing where and how energy is being used in the community. Results are presented for total electricity use, natural gas use, and TDV energy use.

tial building types resemble aerospace manufacturing minus the cooling load.

In general, these load shapes follow expected hourly profiles, with nonresidential building energy loads peaking during normal business hours. Nonresidential space heating peaks in the morning when thermostat settings change to warm buildings for business operating hours. Cooling loads peak in the early afternoon. Residential electrical loads peak in the early evening while gas loads have dual peaks in the morning and early evening.

One obvious difference between the single- and multifamily load profiles is the repetition of daily load shape for the multifamily BEM. Due to differences in BEM modeling (i.e., stochastic occupancy modeling for single family), single-family load shapes are not regularly repeated during the simulation. This attribute is further explored in Fig. 13, which shows the range of load profiles generated across all single-family buildings captured in the community energy model. This figure shows the average load for these buildings, the 25 % and 75 % percentile load shape envelope, and the maximum sand minimum load at each time step.

Additional residential sector results are shown in Fig. 14. This figure shows energy end-use across electricity and natural gas. Gas space heating, which is not shown, uses 4,602 MMBtu per year per residence. A breakdown of all other building types is provided in the appendix.

5.3. Electrical distribution system

The predicted electrical demand for each BEM was aggregated at the transformer level. These loads were then fed into the ACPF simulation described in Section 4.5. Results from the simulation were used to ensure that voltage and ampacity constraints were respected. Two boxplots depicting per unit secondary voltage (or at the delivery voltage) and cable ampacity are shown in Fig. 15. The x-axis of the figure indicates the start of branch circuits shown

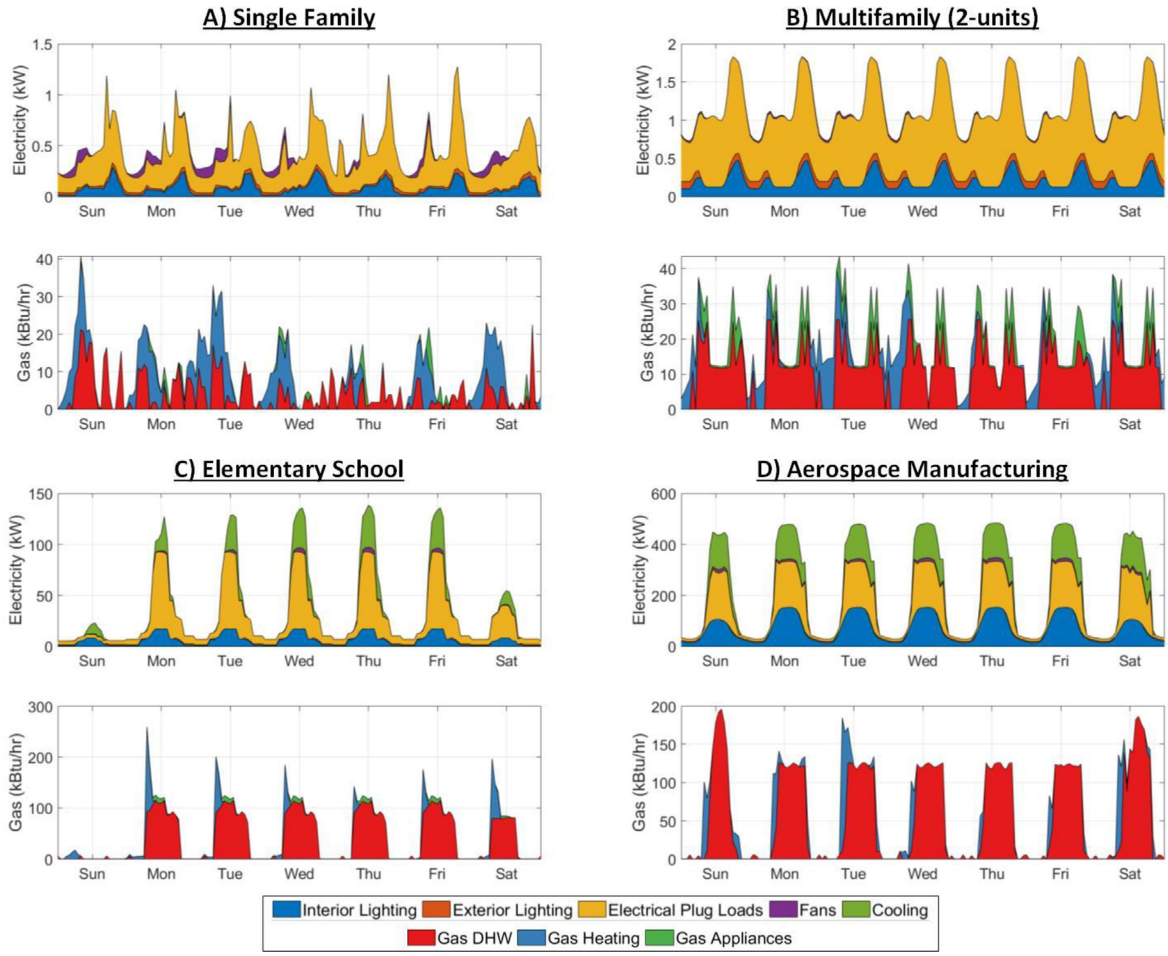

Fig. 12. Examples of DEER standard BEM electric and natural gas use dynamics for different building types for a week in January. Buildings include a) single family, b) multifamily, c) elementary, and d) aerospace manufacturing. The aerospace manufacturing load dynamics are representative of other commercial and industrial buildings. Plots show operation during a winter week, showing space heating operation in all building types. Results also show space cooling operation to offset internal heat gains. Although this operation is a product of model limitations described in Section 5.1, cooling system dynamics are like summer operation. X-axis ticks are located at 12 pm noon each day.

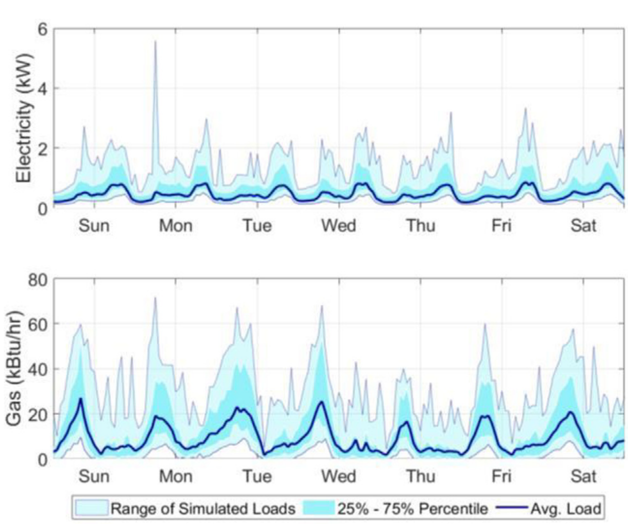

Fig. 13. The range of electricity and natural gas loads captured in the single-family BEM workflow during a winter week. The figure shows the average load across all single-family buildings, the range of loads captured between the 25th and 75th percentile during each time step, and the complete range single-family simulation results.

in Fig. 8. Smeltzer circuit branch circuits are labeled as 'SR1', 'SR2', 'SR3', 'SR4', 'SR5', and 'SR6'. The lone Standard branch circuit is labeled as 'SD1'. Transformers and cables for each branch are shown in order of proximity to the start of each branch circuit. Annual secondary voltage and cable ampacity simulation results for all circuit branches and nodes are shown using boxplots. The middle red line in each box plot indicates the median annual value. The 25th and 75th percentile values are shown as the bottom and top of each box, respectively. All regular data falls within the whiskers and extreme data points as red '+' markers..

The top subplot in Fig. 15 shows that per unit secondary voltage distribution for all active nodes always within acceptable limits, ranging between 0.998 and 0.983 p.u. respectively. The bottom subplot in Fig. 15 shows the line-to-line ampacity for all active branch circuits. Assuming copper conductors, all residential circuits can safely use 6-gauge. The commercial and industrial circuit ("SR6"), however, requires 1-gauge cable at the start of the circuit, followed by 2-gauge and 6-gauge cable sizes along the remainder of the length of the circuit. Only 6 % of total SR6 cable length is comprised of 1-gauge cable.

6. Discussion

The goal of this work is to demonstrate a replicable and scalable method for simulating energy use across an atypical community

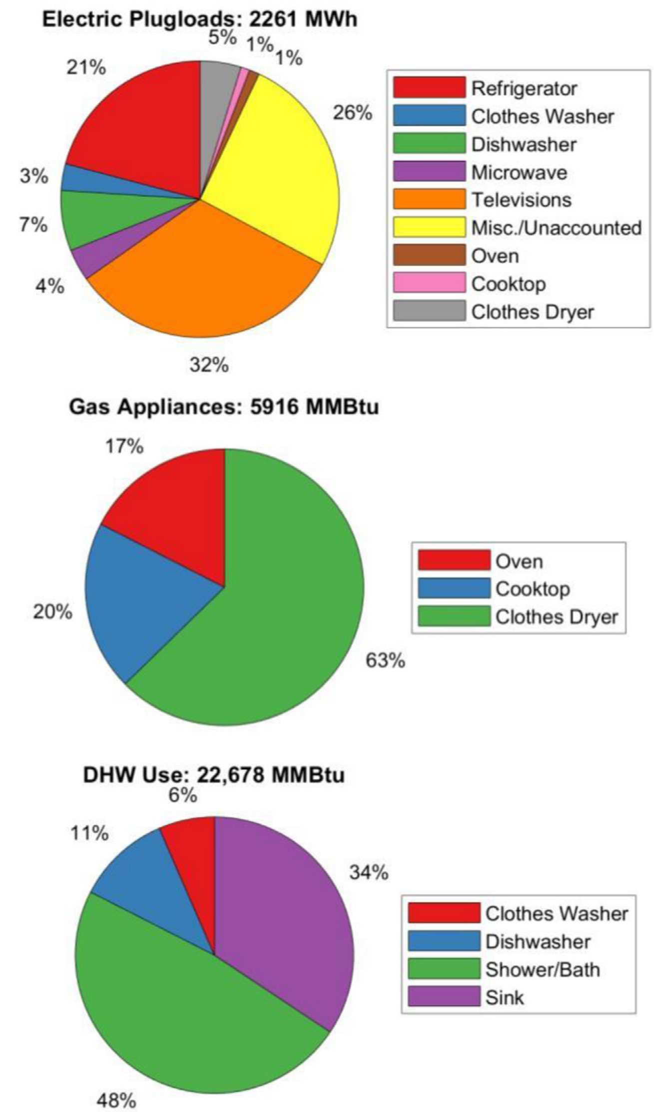

Fig. 14. Pie charts showing end use breakdowns for annual energy use in the residential sector. Results are shown for electric and natural gas use. Since DHW loads have a large impact on community wide energy use, natural gas results are split between gas appliances and DHW use. Gas space heating, which is not pictured here, uses 4,602 MMBtu per year across all residential buildings.

with minimal private data input. Four factors that require discussion are the extent to which private data can be avoided altogether, the accuracy of the building and community scale energy models, model extensibility and scalability, and the potential value of including an ACPF model. Two other outcomes from this work were 1) the mismatch between prototype energy models and annual energy use in the low-income Oak View community, and 2) the difference in TDV energy use between residential and commercial/industrial buildings. This highlights the care and effort that must be made to accurately model energy use in neighborhoods with different socioeconomic characteristics compared to the general population. Additionally, this highlights the need to focus on residential buildings to address building energy and climate goals.

6.1. Data availability

Aside from tax lot and anonymous residential utility data, all other data sources used in this work are publicly available or can be generated through site visits involving minimal resident interaction. Tax lot and utility data were critical to model development and were made available through a partnership between researchers and the City of Huntington Beach. Additionally, knowledge gained through energy audits of approximately 10 % of all Oak View residential units was necessary for critical internal evaluation of model outputs. These audits were made possible through our partnership with the City, which had immediate contact and attention from Oak View property owners.

Local governments are moving to create new datasets that are useful in the developing of community-scale energy models. Examples include energy disclosure requirements and data sharing, searchable and downloadable tax lot information databases, building geometry files, and other data products. Based on our project experience, initial development of any community-scale energy model should include consultation with local governments at the city and county level to reduce model development time and to speed up and improve any necessary interactions with community residents. The key tools, data, and initiatives used in this work include 1) the collection anonymous utility data, 2) tax lot and building geometry information, 3) a bottom-up load estimation process [52], 4) energy use survey data [3], and 5) an effort to perform on-site energy audits. In this case study, the energy audit covered approximately 10 % of all residential units in the community, and resulted in critical insight on building envelope, HVAC and DHW systems, existence of plug loads, lighting density, and thermostat setpoints.

6.2. Accuracy of energy models

In the author's estimation, prototypical BEMs perform poorly in this work due to a lack of nuance and understanding of how energy use in a low-income community differs from standard modeling assumptions. A prime example are plug loads, which are estimated to be far lower in Oak View than estimates for a typical residential [3,44]. By definition, the purpose of a prototype BEM is to develop a general approximation of how energy is used in a typical building. This leads to the clear need for BEM tuning in order achieve any level of acceptable accuracy at the community scale (<10 % error). Section 5.1 demonstrated that additional tuning based on energy survey and energy audit data can achieve a high level of accuracy on both an annual and monthly basis. While the model tuning efforts presented in this paper are specific to the Oak View Community, the model tuning methods, associated data sources, and energy audit approaches presented in this paper can be leveraged in future site specific studies to arrive at a more robust and accurate community models that mimics energy use predictions for disadvantaged communities than would otherwise be achieved through the use of prototypical models.

Current efforts were limited to tuning at the community level only. However, the measures and processes used for community scale tuning described in Section 3.1.2 and 3.1.4 adjust individual building loads. These methods are immediately useful for tuning of individual BEMs when detailed submeter energy data is available.

When submetered building energy data is not available, it is likely preferrable to use a stochastic approach like the single-family OS-HPXML workflow. This workflow, which generates loads using Markov chains based on real usage data [31], generates residential load profiles that can capture critical features of realistic load dynamics. These stochastic processes were developed using real residential building data and were previously shown to replicate residential energy load dynamics.

This approach does not ensure accuracy when compared to real building data but is designed to capture stochastic and cyclical energy dynamics present in real buildings. Furthermore, if load characteristics (i.e., peak load, dynamics, and total energy) are cap-

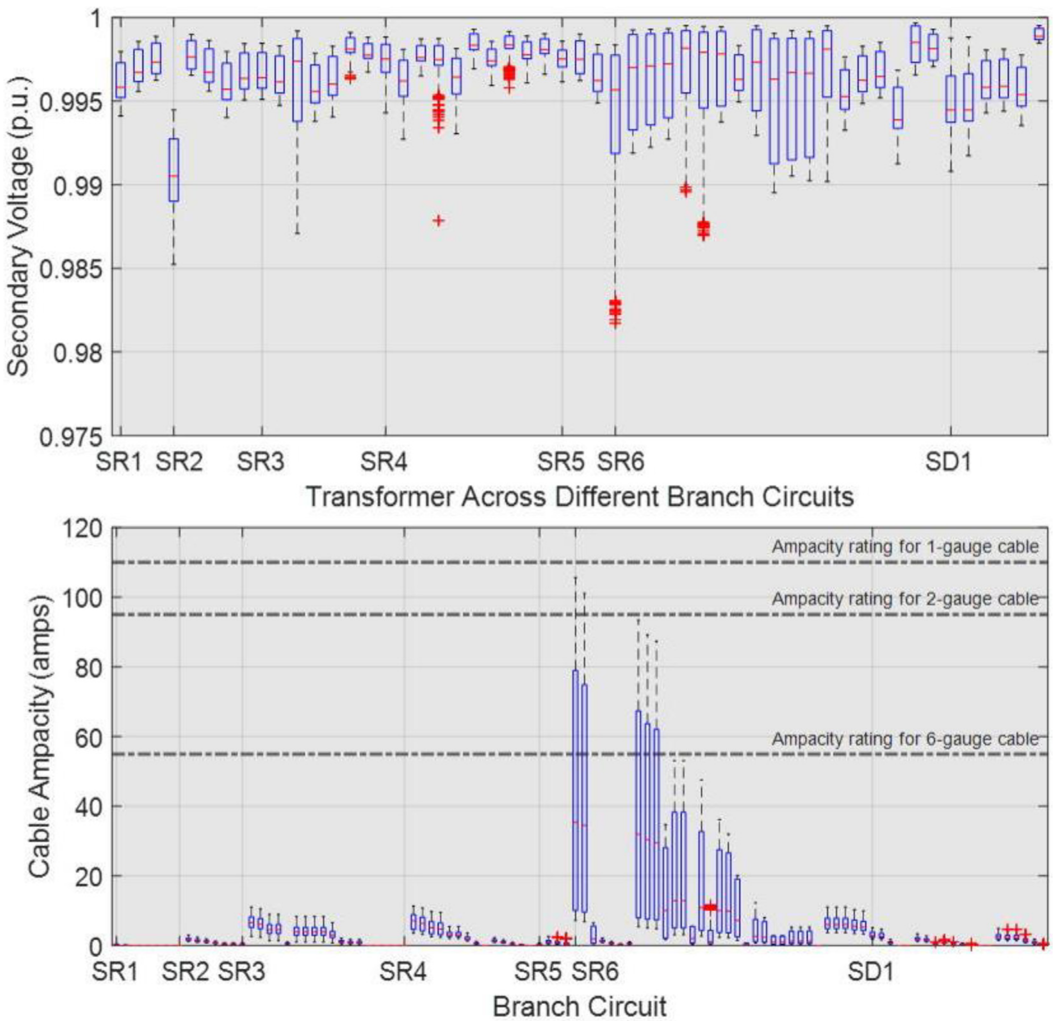

Fig. 15. Per unit secondary voltage distribution and line ampacity across all nodes, transformer and, cables in the Oak View Community ACPF.

tured using this method, quality, and reliability of clean energy technology analyses from CBEM approaches is likely to improve without needing detailed hourly load profiles from each individual building.

6.3. Community model scalability and extensibility

The current model captures a large community design area of 317 buildings covering 2.36 million square feet finished floor area. Simulations ran to completion in approximately 45 min when using a machine with 20 2.80 GHz processors. Simulation result files were reduced to Matlab data objects that were up to 400 MB in size (or 1.3 MB per building per simulation) and contained time resolved, disaggregated load profiles and interior zonal temperatures for all buildings.

Depending on the types of clean energy technologies considered in a CSEM or UBEM, this level of detail may be unnecessary and black box BEM (i.e., statistical or machine learning based BEMs). However, more complex measures that require interaction between building thermal zones and energy systems will likely require detailed physical models prior to black box model development. An example of this is the integration of a hot water heat pump into a building space cooling system, or the development of more complex BEM workflows (i.e., single family OS-HPXML).

The current approach is also extensible to different regions and technologies. First, URBANopt uses weather inputs that can be tailored to specific climates and areas using existing open source BEM development tools [71,72]. Existing BEM templates can be changed to better represent building stock in different regions, and BEM structural components (e.g., opaque exterior and fenestration features and properties) can be fine-tuned using existing OpenStudio. Second, current measures can be modified to capture new clean energy technologies. In instances where existing measures are insufficient to capture the physics of emerging clean energy technologies and applications, new measures can be developed in the traditional OpenStudio and EnergyPlus environments, followed by community scale examination using URBANopt.

7. Summary and conclusions

This paper presents a process for developing a community scale energy model for a disadvantaged community located in Huntington Beach, CA. The modeled community includes 286 single and multifamily residential buildings and 31 commercial, industrial, and educational buildings. The community-scale energy model includes individual BEM for all buildings, and an AC power flow model of the local electrical distribution circuits.

Community scale energy model tuning is accomplished through the individual tuning of each BEM. Commercial, industrial, and educational BEM are tuned to match annual energy use values suggested by commercial building energy surveys. Residential buildings are tuned using a combination of energy survey data, building energy model prototype standards (i.e., Building America), and energy audit results. This approach allows for detailed load construction, setting the stage for the analysis of energy efficiency measures, electrification, and onsite renewable energy conversion and storage technologies. BEM workflows used in this work included a new detached single-family BEM approach that uses a stochastic building load development approach based on real building energy data.

Important outcomes from this work are:

- This work demonstrates the development of an accurate low-income community-based energy model using publicly available data or accessible with support from local governments. While results are specific to the case study presented in this work, necessary data inputs are widely available, and the approach is replicable in different cities and climate zones.
- Special care must be taken when simulating a disadvantaged and low-income community. For the community in this study, the application of prototype energy model standards yielded a predicted aggregated residential electricity demand 54 % higher and natural gas use 28 % lower than actual use. This error was reduced through the development of a bottom-up load construction approach based on site information and visits, energy survey data, and building energy modeling standards. The combination of the approach with community interaction led to critical model tuning steps, such as modification of miscellaneous plug loads and DHW demand.
- At the community level, the proposed modeling approach captures the dynamics of monthly energy use across the residential sector. This is accomplished through the tuning of loads on an annual basis. Typical monthly error between aggregate BEM and actual residential building energy use is less than 10 %.
- The individual BEM tuning method can be readily employed to incorporate real building energy use data. This creates the potential to improve BEM accuracy as higher quality data becomes available.
- The resulting model captures both the physics of building energy use and interaction with the local electric distribution system. The model is ready to examine the impact of energy efficiency, electrification, and renewable DER systems. The model is also suitable for integration with transportation models that can capture the introduction of electric vehicles into the local energy system.

Data availability

Data will be made available on request.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors gratefully acknowledge the financial support for this work, which was provided by the California Energy Commission, contract number: EPC-17-045, and the significant leadership and contributions of our current contract manager, Elise Ersoy, and our former contract manager Eric Ritter.

The authors also gratefully acknowledge support from the City of Huntington Beach, and the support provided by Antonia Graham, Catherine Jun, and Abraham Torres.

This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Building Technologies Office. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

Appendix

This appendix describes the benchmarks used for tuning individual buildings inside the community scale energy model. Equations from the NREL Building America document were used as the basis for developing residential energy loads, while the DOE CBECS survey was used as the basis for all nonresidential loads.

Residential Lighting: The original lighting baseline in the NREL Building America document assumes a lighting mix of 66 % incandescent, 21 % compact fluorescent, and 13 % linear fluorescent. Lighting efficiency standards implemented in 2020, which required for typical residential lighting to operate at 45 lm per watt or higher [73], have eliminated the sale of new incandescent lighting for use in common lighting fixtures used for conventional lighting purposes. As a result, the baseline was altered to eliminate incandescent lighting with compact fluorescent.

The following sets of equations were used to develop annual energy used for interior and exterior lighting. Eq. (1) predicts total interior lighting based on interior floor area and an adjustment factor based on types of bulbs used. This factor is predicted by Eq. (2). Note that Eq. (2) is adjusted from the original equation reported in [52] to account for the removal of incandescent light bulbs from the baseline. This equation also factors a 10 % increase in lighting as energy efficient bulbs are adopted. Other factors in Eq. (2) are F_{CFL} and F_{LF}, or the fraction of lighting that is compact fluorescent and linear fluorescent, respectively. These values are set to $F_{CFL} = 0.87$ and $F_{LF} = 0.13$. These values assume that all incandescent bulbs are replaced using compact fluorescent, not linear fluorescent. Exterior lighting is predicted using Eq. (3).

$$InteriorLighting = \eta_{lighting}(0.542 * FFA + 334)kWh/year \tag{1}$$

$$\eta_{lighting} = (0.34 + 0.27 * (F_{CFL} - 0.21) + 0.17 * (F_{LF} - 0.13)) * 0.9 + 0.1 \tag{2}$$

$$ExteriorLighting = \eta_{lighting} * 0.145 * FFAkWh/year \tag{3}$$

Note that the Building America protocol recommends that a more detailed analysis be conducted for multifamily building than what is presented in Eqs. (1) through (3) due to the presence of common areas (i.e., shared laundry facilities). However, this approach was not taken because 1) many of the multifamily buildings lack a traditional common area, placing laundry facilities in shared garage spaces, and 2) floor plans and space end use designations were not available for many of the properties, both of which are needed for a more detailed analysis.

According to this model, the average Oak View multifamily residential unit (FFA = 1240 ft^2) will have an annual interior lighting load of 571 kWh per year, and an exterior lighting load of 102 kWh per year.

Residential Electrical Plug Loads and Electrical Equipment: The following types of electrical appliances were assumed to be present in every residential unit operating at a fixed energy use per year:

- Single refrigerator: 434 kWh/year
- Microwave: 78 kWh/year
- Television(s): 673 kWh/year

Additional electrical plug loads assumed to be present in each unit were dishwashers[6] and "miscellaneous" plug loads, which were predicted using Eqs. (4) and (5) respectively, where N_{br} is the number of bedrooms in a residential unit. According to these predictions, the average multifamily residential unit would use 146 kWh per year to power a dishwasher, and 2653.96 kWh per year on miscellaneous electrical loads. Most properties include shared laundry facilities, leading to the assumption that loads associated with clothes washing occur onsite. Eq. (6) was used to predict clothes washer electrical energy use, producing an annual demand of 64.6 kWh per year for an average residential unit.

$$Dishwasher = 87.6 + 29.2 * N_{br} kWh/year \tag{4}$$

$$Misc.PlugLoads = 1595 + 248 * N_{br} + 0.454 * FFA kWh/year \tag{5}$$

$$ClothesWasher = (38.8 + 12.9 * N_{br}) kWh/year \tag{6}$$

Site visits and energy audits showed that most residential buildings provide gas for range and clothes dryer operation at most buildings except for the five fully electrified buildings. Electrical energy use for electric oven, cooktop, and clothes dryer use is shown in Eqs. (7), (8), and (9) respectively. Oven and cooktop efficiencies are captured using the η terms. According to these equations, the average Oak View multifamily residential unit would use 222 kWh per year to power an oven, 195 kWh per year to power a cooktop, and 897 kWh to operate a clothes dryer.

$$Oven = \frac{14.6 + 4.9 * N_{br}}{\eta_{Oven,electric}} kWh/year \tag{7}$$

$$Cooktop = \frac{86.5 + 28.9 * N_{br}}{\eta_{Cooktop,electric}} kWh/year \tag{8}$$

$$ClothesDryer = 538.2 + 179.4 * N_{br} kWh/year \tag{9}$$

Residential Gas Appliances and Equipment: Aside from the five electrified buildings, all other residential buildings are assumed to use natural gas to power ovens, cooktops, and clothes dryers. Gas use in these appliances is predicted using the Eqs. (10) through (12). Oven and cooktop efficiencies are captured with η terms. Clothes dryer efficiency is captured using $ef_{elecdryer}$ and $ef_{gasdryer}$ for electric and gas appliances, respectively. These terms have units kWh energy input per pound of damp, clean laundry processed and According to these predictions, the average Oak View multifamily residential unit will use 5.375 therms of natural gas in an oven, 10.5 therms on a cooktop, and 39 therms of natural gas in a clothes dryer, per year.

$$Oven = \frac{0.44 + 0.15 * N_{br}}{\eta_{Oven,gas}} therms/year \tag{10}$$

$$Cooktop = \frac{2.64 + 0.88 * N_{br}}{\eta_{Cooktop,gas}} therms/year \tag{11}$$

$$ClothesDryer = \frac{1therm}{29.3kWh}(538.2 + 179.4 * N_{br}) * \frac{ef_{elecdryer}}{ef_{gasdryer}} therms/year \tag{12}$$

Note that these appliances also require electricity for operation. However, electricity usage in gas appliances was not captured for three reasons: 1) electricity requirements for gas appliances are estimated to be between 85 % and 95 % lower than the comparable electrical only appliance and is small relative to other loads, 2) application of energy efficiency tuning measures are projected to have a minimal impact on electricity use in natural gas appliances, and 3) energy simulation tuning measures aimed at modeling energy efficient natural gas appliances primarily reduce gas use, not electricity. As a result, it is assumed that the electrical load associated with natural gas appliances is captured in the miscellaneous electrical plug load prediction model presented in Eq. (5).

Residential Domestic Hot Water: Domestic hot water (DHW) loads depend on usage patterns and fuel source. Usage patterns are assumed to be independent of fuel source and depend solely on residential unit characteristics and water heater setpoint. This work assumed that the DHW heater setpoint is 140°F. Appliances that use hot water directly from the DHW heater are clothes washing machines and dishwashers. Common clothes washers in multifamily buildings are assumed to require 2.47 gallons per day per residential unit. Hot water use for dishwashers is shown in Eq. (13), predicting that the average multifamily residential unit will use 3.76 gallons of hot water per day.

$$DishwasherHotWater = 2.26 + 0.75 * N_{br} gal/day \tag{13}$$

Other hot water uses include water use in showers, baths, and sinks. The target temperature is assumed to be 110°F. If cold water comes out of the tap at 60°F, 0.625 gallons of each gallon pulled from a faucet comes from the DHW system at 140°F. This factor was applied to predict total DHW requirements for a residential unit using Eqs. (14) through (16). According to these predictions, the average multifamily residential unit would use 14.6 gallons hot water per day to meet shower demand, 3.65 gallons to meet bath demand, and 13 gallons to meet sink demand. Total DHW hot water demand is predicted to be 37.5 gallons hot water per day.

$$ShowerDemand = 0.625(14 + 4.67N_{br}) gal/day \tag{14}$$

$$BathDemand = 0.625(3.5 + 1.17N_{br}) gal/day \tag{15}$$

$$SinkDemand = 0.625(12.5 + 4.15N_{br}) gal/day \tag{16}$$

Using a water density of 8.345 lb per gallon of water and a specific heat C of 1 $\frac{Btu}{lbR}$, energy input was determined using Eq. (17). Using the appropriate efficiency, an average residential unit with an electric resistive tank water heater is projected to use 3108 kWh per year, and 154 therms with a natural gas tank water heater.

$$DHWEnergy = 365 * \frac{DHWDemand * 8.314 * (140^oF - 60^oF)}{\eta_{DHW}} btu/year \tag{17}$$

Other Residential End Uses: The Building America documentation includes other end use specifications, most notably whole house and spot ventilation fans. These energy load predictions were not developed because they do not correspond to a tunable load in the community scale energy simulation. Instead, additional loads, such as ventilation fans, were assumed to be a component in miscellaneous plug loads and are not directly accounted for.

[6] Dishwasher energy use consists of electricity used to operate the system plus energy required to heat water used in the dishwasher. This plug load prediction only captures electricity used to operate the system. Energy used to heat water is captured in the subsequent prediction for domestic hot water heating.

Residential Heating, Cooling and DHW Performance Properties: The following properties were used to define the baseline performance of all heating, cooling, and DHW systems across all BEMs.

- All buildings use tank DHW heaters. Gas and electric DHW heater efficiencies are 78 % and 98 %, respectively, resulting in a DHW uniform energy factor of 0.6 for gas and 0.9 for electric water heaters.
- Gas furnaces in residential and small commercial/industrial have a fuel to heat conversion efficiency of 78 %. Electric resistive heaters have an electricity to heat conversion efficiency of 98 %.
- Larger commercial/industrial buildings using a boiler for space heating have an 80 % fuel to heat conversion efficiency.
- Residential central air conditioning systems operate with a coefficient of performance of 3.14. Commercial and industrial buildings use an air-cooled chiller with a coefficient of performance of 2.8.

Residential Thermostat Tuning: Tuning of the heating and cooling thermostat settings depends in part on annual weather conditions. Average daily dry bulb temperature is shown in Fig. 16 for the TMY3 and actual weather from 2016 and 2020. This figure shows that TMY3 data trends colder than recent weather except for a handful of days.

Commercial and industrial thermostat data is limited, and heating and cooling energy use intensities vary greatly between relevant buildings in the DOE CBECS data set. As a result, the standard thermostat setpoints defined in the DEER BEM template were used for this work. Heating setpoints of 70°F between 7 a.m. and 7p.m., and 64°F during all other hours were assumed.

The 2015 DOE RECS data were used to develop thermostat settings for all residential buildings. Heating loads for all residential buildings were tuned to match DOE RECS data. Cooling loads for the six buildings with central air conditioning were also tuned to the same dataset. Discussions with tenants during site visits revealed large differences in how tenants use their heating systems with several tenants reporting that they rarely heat their homes. Differences in thermostat settings and HVAC system use patterns, however, were not included in the current work due to difficulty in implementing different thermostat settings within the same building paired with insufficient data to determine how the thermostat in each residential unit is set. Rather, the average impacts of varying thermostat settings within the residential building stock are captured. Details on how the energy use targets were developed using the DOE RECS data are provided below. The resulting heating thermostat settings were changed to 69.3°F for buildings with natural gas space heating, and 70°F for buildings with electric resistive space heating. Note that the heating thermostat setting for buildings with electric resistive heating systems resulted in an annual heating EUI approximately 50 % lower than DOE RECS values. However, simulation results did not match the DOE RECS target unless the thermostat was increased to 74 °F. This setting was deemed unrealistic based upon discussions with residents. Cooling thermostat settings were changed to 79 °F, again reflecting the overall average of settings within the residential building stock required to match the DOE RECS data.

The DOE RECS target was developed by filtering survey data by region (pacific), building (multifamily), and equipment type (built in wall and central natural gas furnace). The resulting filtered data was then separated by heating degree days (HDD). The resulting data in total and binned by HDD is shown in Fig. 17 for residential units with gas heaters. This figure shows a box plot, indicating a red line at the average of each binned group of data, the 25 % and 75 % percentile for the binned data at the top and bottom of each box, the 0 % and 100 % at the end of the vertical hashed marks, and outliers as red "+" symbols. The Oak View Community typically has between 1400 and 1600 HDD per year [74]. Since total HDD varies from year to year, the average of the 1 K-1.5 K HDD and 1.5 K-2 K HDD binned groups was taken as the target energy intensity of 5 kBtu per year per ft^2, or 0.05 therms per year per ft^2. For the average Oak View residential unit, this translates to 62 therms per year for space heating. Note that the RECS data shows large fluctuations in heating energy intensity, with the 75 % of the 1.5 K-2 K bin being nearly double the assumed heating intensity.

The DOE RECS data set has limited data on multifamily buildings with electric resistive heating. However, this estimate is necessary for the five buildings with electric resistive space heating. Taking the average of the available data in an appropriate HDD range (+/−1000 HDD) yielded an energy intensity of 0.85 kWh per year per ft^2. After considering assumed heater efficiencies, this value is 25 % lower in delivered heating versus the gas heating energy intensity. Explanations for this difference is not clear but could be due to the high cost of electricity relative to natural gas resulting in less space heating, the use of individually controlled baseboard electric heaters that are turned on when certain rooms are occupied, or a lack of representative electric resistive heating data.

The same method for estimating space heating was applied to predicting space cooling. Space cooling results for multifamily buildings with central air conditioning in the Pacific region from

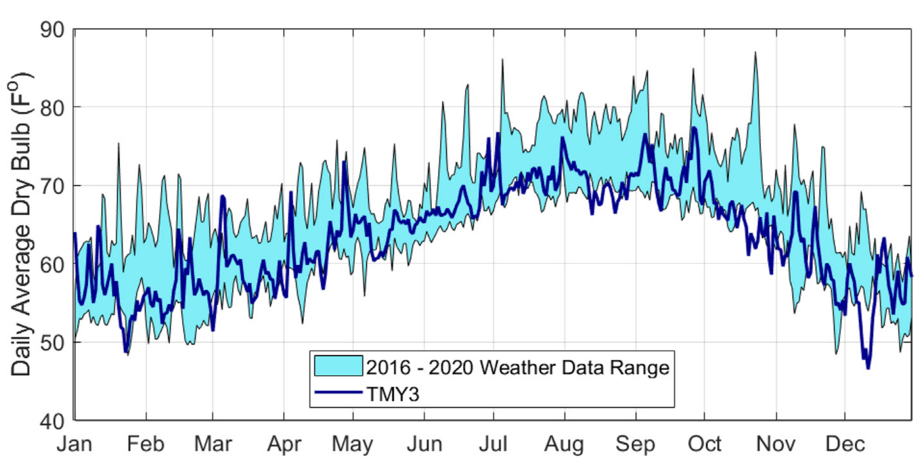

Fig. 16. A comparison of average daily temperature from the TMY3 Long Beach Airport dataset against the range of average daily temperatures experienced in the same location between 2016 and 2020. The comparison shows that the TMY3 dataset for this location tends to be colder than recent actual weather.

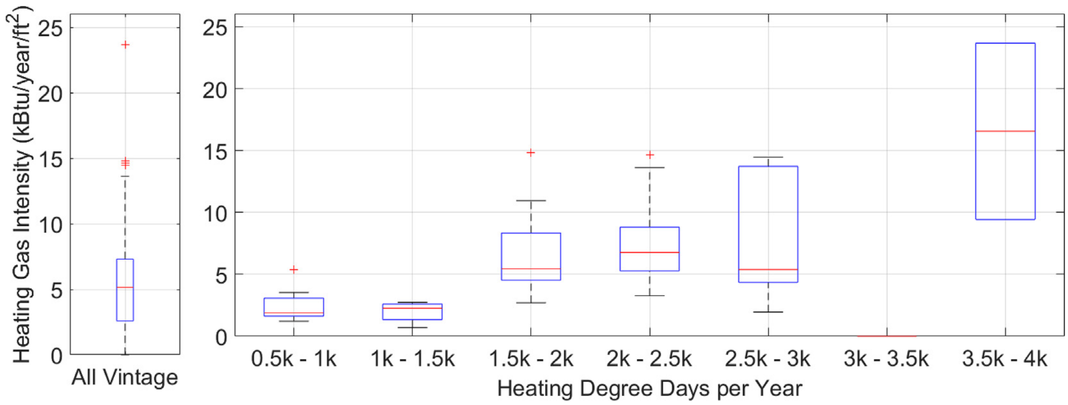

Fig. 17. Gas heating intensity versus HDD derived from the DOE RECS data set.

the DOE RECS dataset is shown in Fig. 18. The Oak View Community is characterized as having approximately 1200 cooling degree days per year. Using this value, the average energy intensity from the binned data group spanning 1 K-1.5 K CDD was taken, giving a cooling energy intensity of 0.5 kWh per ft^2 per year, or 620 kWh per year for the average Oak View residential unit. This cooling energy intensity was applied only to the six buildings with central air conditioning.

Although individual air conditioners are neglected in the baseline model, the DOE RECS data set was also filtered to yield an energy intensity for individual air conditioners user in climates like Oak View. The results indicated that an individual air conditioner would require approximately 250 kWh per year to operate and would condition between 200 and 350 ft^2.

Using these results, residential thermostats were tuned such that community scale heating and cooling energy intensity matched the average values derived from the DOE RECS data: Thermostat adjustments were made against the stock thermostat settings from the DEER BEM multifamily and single-family BEM templates. The base heating thermostat value for buildings with natural gas heaters was increased from 68°F to 69.3°F. The cooling thermostat value for buildings with central air conditioning was decreased from 80°F to 79°F. Thermostat settings for the five buildings with electric resistive heaters were increased from 68°F to 70°F. Despite the increased thermostat setting, the heating energy intensity is approximately half the value predicted by the DOE RECS data. In fact, a heating thermostat setting of 74°F or higher was required to reach heating energy intensity targets. This value was deemed unrealistic and ignored.

Commercial and Industrial Buildings: The DOE CBECS survey was used to develop target energy use intensities (EUIs) for commercial and industrial buildings. The CBECS data was filtered to examine buildings that were like what is found in the Oak View community. Target EUIs were then found by taking the weighted average of the remaining data. FFA was used as the weighting factor. The following describes how the CBECS data was filtered and the resulting EUI's.

Educational: The CBECS data was filtered as follows:

- Limited to the Pacific census division
- School building floor area was limited to 10,000 ft^2 or less
- School buildings are only used for "one activity," i.e., for typical school activities
- Operation is limited to 60 h per week
- Between 75 % and 100 % of all floor area is lit during typical operating hours
- Lights are not on 24 h a day
- Lighting is reduced during off hours
- Linear fluorescent lighting is used in 98 % or more fixtures

Using these filtering parameters, the following EUIs were developed:

- Interior lighting: 1.2 kWh per ft^2 per year
- Plug loads: 4.44 kWh per ft^2 per year, which consists of:
- Refrigeration: 0.9 kWh per ft^2 per year
- Office equipment: 0.36 kWh per ft^2 per year
- Computers: 2.3 kWh per ft^2 per year
- Miscellaneous: 0.88 kWh per ft^2 per year

These EUI targets were applied to all buildings shown in Fig. 1 inside the polygons surrounding the Oak View Elementary and Family Resource Center & Library buildings.

Office: The CBECS data was filtered as follows:

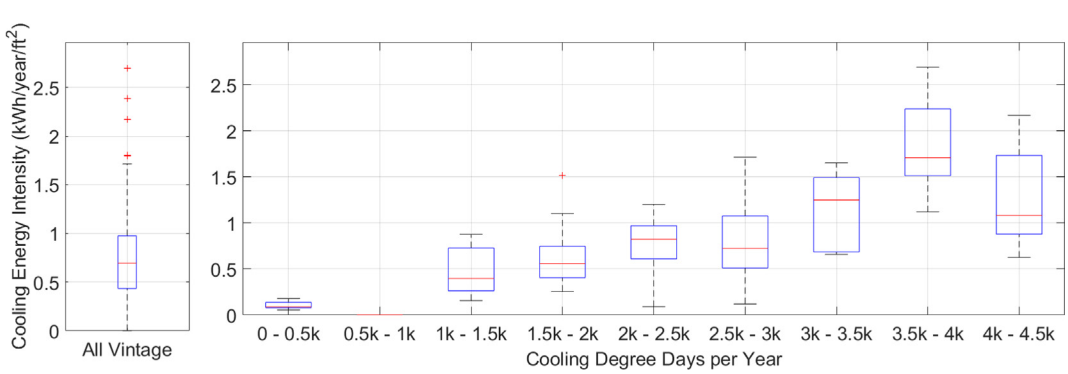

Fig. 18. Space cooling intensity versus HDD derived from the DOE RECS data set.

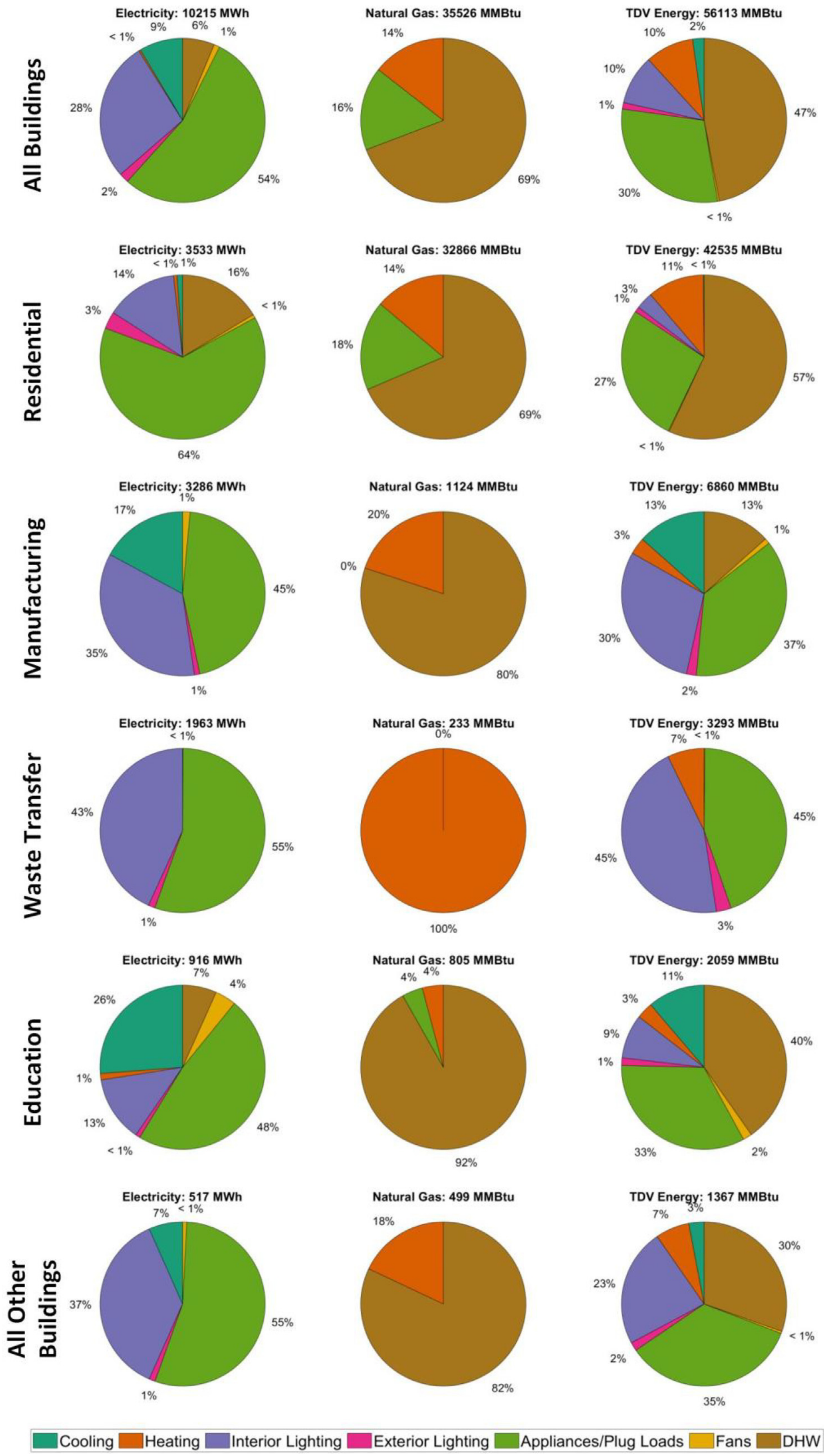

Fig. 19. Breakdown of energy end uses across the simulated community and within individual building types.

Table 3
Transformer ratings required for stable and reliable electrical distribution service across the Oak View community.

Transformer Name	Transformer Rating (kVa)	Transformer Name	Transformer Rating (kVa)	Transformer Name	Transformer Rating (kVa)
S1	75	S24	50	T2	50
S2	25	S25	37.5	T3	150
S3	25	S26	25	T4	150
S4	50	S27	25	T5	150
S5	25	S28	50	T6	75
S6	75	S29	50	T7	1500
S7	50	S30	50	T8	25
S8	50	S31	25	T9	150
S9	50	S32	25	T10	100
S10	100	S33	100	T11	300
S11	100	S34	50	T12	50
S12	50	S35	50	T13	350
S13 & S14	150	S36	25	T14	75
S15	50	S37	100	T15	50
S16	100	S38	50	T16	150
S17	25	S39	50	T17	25
S18	112.5	S40	25	T18	300
S19	50	S41	25	T19	25
S20	37.5	S42	50	T20	300
S21	50	S43	25	T21	150
S22	50	S44	112.5		
S23	50	T1	50		

- Total building floors is two or less
- Between 75 % and 100 % of all floor area is lit during typical operating hours
- The building is used between 30 and 80 h per week
- Linear fluorescent lighting is used in 98 % or more fixtures

Using these filtering parameters, the following EUIs were developed:

- Interior lighting: 1.9 kWh per ft^2 per year
- Plug loads: 4.86 kWh per ft^2 per year, which consists of:
- Refrigeration: 0.21 kWh per ft^2 per year
- Office equipment: 0.73 kWh per ft^2 per year
- Computers: 2.3 kWh per ft^2 per year
- Miscellaneous: 1.52 kWh per ft^2 per year

These EUI targets were applied to all office buildings.

All other nonresidential buildings: All other nonresidential building baselines were modeled as an "automotive repair shop." The CBECS data was filtered as follows:

- Total building floors is two or less
- Between 75 % and 100 % of all floor area is lit during typical operating hours
- The building is used between 30 and 80 h per week
- Linear fluorescent lighting is used in 98 % or more fixtures

Using these filtering parameters, the following EUIs were developed:

- Interior lighting: 2.7 kWh per ft^2 per year
- Plug loads: 3.46 kWh per ft^2 per year, which consists of:
- Refrigeration: 0.4 kWh per ft^2 per year
- Office equipment: 0.33 kWh per ft^2 per year
- Miscellaneous: 2.73 kWh per ft^2 per year

These EUI targets were applied to all non-office and educational buildings.

After tuning the baseline model to match these EUI and Building America load targets, the community scale energy simulation produced the results shown in Fig. 19. This figure shows the breakdown of annual energy by end use. These results predict end use energy across the community in preparation for studying the impact of DER, electrification, and energy efficiency on the community.

Finally, the transformer ratings used in the Oak View ACPF model are shown below in Table 3. The ratings are based on field observations combined with simulate results. During ACPF simulation, transformer ratings were adjusted as needed to ensure all system components are never overloaded. Overloaded electric distribution circuit components tend to fail faster due to periods of thermal stress beyond system design limits.

References

[1] Y.Q. Ang, Z.M. Berzolla, C.F. Reinhart, From concept to application: A review of use cases in urban building energy modeling, Appl. Energy 279 (2020), https://doi.org/10.1016/j.apenergy.2020.115738.

[2] L.N. Dwaikat, K.N. Ali, Green buildings cost premium: A review of empirical evidence, Energ. Buildings 110 (2016) 396–403, https://doi.org/10.1016/j.enbuild.2015.11.021.

[3] U.S. Energy Informaiton Administration. 2015 Residential Energy Consumption Survey (RECS) - Energy Information Administration 2015. https://www.eia.gov/consumption/residential/index.php (accessed February 9, 2021).

[4] U.S. Energy Information Administration. 2012 Energy Information Administration (EIA)- Commercial Buildings Energy Consumption Survey (CBECS) 2012. https://www.eia.gov/consumption/commercial/ (accessed February 9, 2021).

[5] C.E. Kontokosta, C. Tull, A data-driven predictive model of city-scale energy use in buildings, Appl. Energy 197 (2017) 303–317, https://doi.org/10.1016/j.apenergy.2017.04.005.

[6] J. Roth, A. Martin, C. Miller, R.K. Jain, SynCity: Using open data to create a synthetic city of hourly building energy estimates by integrating data-driven and physics-based methods, Appl. Energy 280 (2020), https://doi.org/10.1016/j.apenergy.2020.115981.

[7] A. Foucquier, S. Robert, F. Suard, L. Stéphan, A. Jay, State of the art in building modelling and energy performances prediction: A review, Renew. Sustain. Energy Rev. 23 (2013) 272–288, https://doi.org/10.1016/j.rser.2013.03.004.

[8] D.B. Crawley, L.K. Lawrie, F.C. Winkelmann, W.F. Buhl, Y.J. Huang, C.O. Pedersen, et al., EnergyPlus: creating a new-generation building energy simulation program, Energ. Buildings 33 (2001) 319–331, https://doi.org/10.1016/S0378-7788(00)00114-6.

[9] M. Deru, K. Field, D. Studer, K. Benne, B. Griffith, P. Torcellini, et al., US Department of Energy commercial reference building models of the national building stock. National Renewable Energy, Laboratory (2011).

[10] K. Field, M. Deru, D. Studer, Using Doe Commercial Reference Buildings for Simulation Studies, SimBuild (2010). 85AD:85–93.

[11] U.S. Department of Energy. Prototype Building Models | Building Energy Codes Program 2016. https://www.energycodes.gov/prototype-building-models (accessed March 17, 2022).

[12] C.F. Reinhart, D.C. Cerezo, Urban building energy modeling - A review of a nascent field, Build. Environ. 97 (2016) 196–202, https://doi.org/10.1016/j.buildenv.2015.12.001.

[13] Christensen C, Horowitz S, Maguire J, Tabares-Velasco P, Springer D, Coates P, et al. BEopt-CA (Ex): A Tool for Optimal Integration of EE, DR and PV in Existing California Homes. National Renewable Energy Lab.(NREL), Golden, CO (United States); 2014.
[14] Y. Chen, T. Hong, M.A. Piette, Automatic generation and simulation of urban building energy models based on city datasets for city-scale building retrofit analysis, Appl. Energy 205 (2017) 323–335, https://doi.org/10.1016/j.apenergy.2017.07.128.
[15] A. Tereci, S.T.E. Ozkan, U. Eicker, Energy benchmarking for residential buildings, Energ. Buildings 60 (2013) 92–99, https://doi.org/10.1016/j.enbuild.2012.12.004.
[16] A. Nutkiewicz, R.K. Jain, R. Bardhan, Energy modeling of urban informal settlement redevelopment: Exploring design parameters for optimal thermal comfort in Dharavi, Mumbai, India. Appl Energy 231 (2018) 433–445, https://doi.org/10.1016/j.apenergy.2018.09.002.
[17] N. Buckley, G. Mills, C. Reinhart, Z.M. Berzolla, Using urban building energy modelling (UBEM) to support the new European Union's Green Deal: Case study of Dublin Ireland, Energ. Buildings 247 (2021), https://doi.org/10.1016/j.enbuild.2021.111115.
[18] Y.Q. Ang, Z.M. Berzolla, S. Letellier-Duchesne, V. Jusiega, C. Reinhart, UBEM.io: A web-based framework to rapidly generate urban building energy models for carbon reduction technology pathways, Sustain. Cities Soc. (2022) 77, https://doi.org/10.1016/j.scs.2021.103534.
[19] Reinhart C, Dogan T, Jakubiec JA, Rakha T, Sang A. Umi-an urban simulation environment for building energy use, daylighting and walkability. 13th Conf. Int. Build. Perform. Simul. Assoc. Chambery, Fr., vol. 1, 2013, p. 476–83.
[20] C. Cerezo Davila, C.F. Reinhart, J.L. Bemis, Modeling Boston: A workflow for the efficient generation and maintenance of urban building energy models from existing geospatial datasets, Energy 117 (2016) 237–250, https://doi.org/10.1016/j.energy.2016.10.057.
[21] J.A. Fonseca, A. Schlueter, Integrated model for characterization of spatiotemporal building energy consumption patterns in neighborhoods and city districts, Appl. Energy 142 (2015) 247–265, https://doi.org/10.1016/j.apenergy.2014.12.068.
[22] J.A. Fonseca, T.A. Nguyen, A. Schlueter, F. Marechal, City Energy Analyst (CEA): Integrated framework for analysis and optimization of building energy systems in neighborhoods and city districts, Energ. Buildings 113 (2016) 202–226, https://doi.org/10.1016/j.enbuild.2015.11.055.
[23] A. Nutkiewicz, Z. Yang, R.K. Jain, Data-driven Urban Energy Simulation (DUE-S): A framework for integrating engineering simulation and machine learning methods in a multi-scale urban energy modeling workflow, Appl. Energy 225 (2018) 1176–1189, https://doi.org/10.1016/j.apenergy.2018.05.023.
[24] A. Nutkiewicz, B. Choi, R.K. Jain, Exploring the influence of urban context on building energy retrofit performance: A hybrid simulation and data-driven approach, Adv Appl Energy 3 (2021), https://doi.org/10.1016/j.adapen.2021.100038.
[25] C. Chen, fei, Xu X, Day JK., Thermal comfort or money saving? Exploring intentions to conserve energy among low-income households in the United States, Energy Res. Soc. Sci. 26 (2017) 61–71, https://doi.org/10.1016/j.erss.2017.01.009.
[26] Chen C fei, Feng J, Luke N, Kuo CP, Fu JS. Localized energy burden, concentrated disadvantage, and the feminization of energy poverty. IScience 2022;25:104139. 10.1016/j.isci.2022.104139.
[27] W. Abrahamse, L. Steg, How do socio-demographic and psychological factors relate to households' direct and indirect energy use and savings?, J Econ. Psychol. 30 (2009) 711–720, https://doi.org/10.1016/j.joep.2009.05.006.
[28] D. Holloway, R. Bunker, Planning, housing and energy use: A review: Practice reviews, Urban Policy Res. 24 (2006) 115–126, https://doi.org/10.1080/08111140600591096.
[29] K.R. El, B. Polly, T. Charan, URBANopt: An Open-source Software Development Kit for Community and Urban District Energy Modeling, Build Perform Anal Conf SimBuild 2020 (2020) 293–301.
[30] B. Polly, C. Kutscher, D. Macumber, M. Schott, From Zero Energy Buildings to Zero Energy Districts, ACEEE Summer Study Energy Effic Build 2016 (2016) 1–16.
[31] J. Chen, R. Adhikari, E. Wilson, J. Robertson, A. Fontanini, B. Polly, et al., Stochastic simulation of residential building occupant-driven energy use in a bottom-up model of the U.S. housing stock. Under Rev, Appl. Energy (2021).
[32] 2010 Census Tract Reference Maps 2010. https://www.census.gov/geographies/reference-maps/2010/geo/2010-census-tract-maps.html (accessed September 29, 2021).
[33] California Climate Investments to Benefit Disadvantaged Communities | CalEPA 2022. https://calepa.ca.gov/EnvJustice/GHGInvest/ (accessed October 1, 2021).
[34] Faust J, Laura A, Komal B, Vanessa G, Julian L, Shankar P, et al. Update to the California Communities Environmental Health Screening Tool CalEnviroScreen 3.0. CalEPA Sacramento, CA, USA 2017.
[35] U.s., Census Bureau, American Community Survey (2019). https://www.census.gov/data.html.
[36] Google Inc. Google Earth v.7.3.4.8248 [Software] 2021.
[37] Polly B, Kutscher C, Macumber D, Schott M, Pless S, Livingood B, et al. From Zero Energy Buildings to Zero Energy Districts. NREL (National Renew Energy Lab (NREL), Goldcn, CO (Unitcd Statcs)) 2016.
[38] Naitonal Renewable Energy Laboratory. HPXML Toolbox 2022. https://hpxml.nrel.gov/ (accessed March 18, 2022).
[39] National Renewable Energy Laboratory. Home - URBANopt Docs 2020. https://docs.urbanopt.net/ (accessed March 17, 2022).
[40] T. Charan, C. Mackey, A. Irani, B. Polly, S. Ray, K. Fleming, et al., Integration of open-source urbanopt and dragonfly energy modeling capabilities into practitioner workflows for district-scale planning and design, Energies 14 (2021) 1–28, https://doi.org/10.3390/en14185931.
[41] ANSI/RESNET/ICC. 2019 ANSI/RESNET/ ICC 380 Standard for Testing Airtightness of Building, Dewlling Unit, and Sleeping Unit Enclosures; Airtightnexx of Heating and Cooling Air Distribution Systems; and Airflow of Mechanical Ventilation Systems. 2019.
[42] National Renewable Energy Laboratory. Residential Workflows - URBANopt Docs 2020. https://docs.urbanopt.net/workflows/residential_workflows/residential_workflows.html (accessed March 29, 2022).
[43] , Single-Family Detached - URBANopt Docs (2022).
[44] Hendron R, Engebrecht C. Building America house simulation protocols 2010.
[45] J. Sanyal, J. New, R.E. Edwards, L. Parker, Calibrating building energy models using supercomputer trained machine learning agents, Concurr Comput Pract Exp 26 (2014) 2122–2133, https://doi.org/10.1002/cpe.3267.
[46] R. Dugan, The Open Distribution System Simulator(OpenDSS), Sourceforge (2020) 1–218.
[47] National Renewable Energy Laboratory. OpenDSS Converter - URBANopt Docs 2020. https://docs.urbanopt.net/workflows/opendss/opendss.html (accessed March 17, 2022).
[48] L. Novoa, R. Flores, J. Brouwer, Optimal DER allocation in meshed microgrids with grid constraints, Int. J. Electr. Power Energy Syst. 128 (2021).
[49] L. Novoa, R. Flores, J. Brouwer, Optimal renewable generation and battery storage sizing and siting considering local transformer limits, Appl. Energy 256 (2019), https://doi.org/10.1016/j.apenergy.2019.113926.
[50] Bartos M, Chester M, Johnson N, Gorman B, Eisenberg D, Linkov I, et al. Impacts of rising air temperatures on electric transmission ampacity and peak electricity load in the United States. Environ Res Lett 2016;11. 10.1088/1748-9326/11/11/114008.
[51] Southern California Edison. Circuit Reliability Review - Huntington Beach 2020. https://library.sce.com/content/dam/sce-doclib/public/reliability/HuntingtonBeach.pdf (accessed August 21, 2020).
[52] E. Wilson, M.C. Engebrecht, S. Horowitz, R. Hendron, Building America House Simulation Protocols, Natl Renew Energy Lab 2014 (2014) 91.
[53] KEMA I. 2009 California Residential Appliance Saturation Study. 2010.
[54] I.T.E.M. Systems, Huang J, Cunningham and Associates, Energy Use And DSM Measure Impacts In Prototypical Buildings, Final Report, 1993.
[55] N.E.O.S. Corporation, Final Report On Technology Energy Savings, Volume I, Baseline Energy Use Characteristics. (1994).
[56] NEOS Corporation. Final Report On Technology Energy Savings, Volume II: Building Prototypes. 1994.
[57] Itron Inc, JJ Hirsh & Associates, Synergy Consulting, Quantum I. 2004-2005 Database for Energy Efficiency Resources (DEER) Update Study. 2005.
[58] E.H. Hamzawi, N. Corporation, M. Messenger, Energy and peak demand impact estimates for DSM technologies in the residential and commercial sectors for California: Technical and regulatory perspectives, Proc. ACEEE 1994 Summer Study Energy Effic. Build. 2 (1994) 145–155.
[59] A. Roth, L. Brackney, A. Parker, A. Beitel, O.BT. OpenStudio, A Platform for Ex Ante Incentive Programs, National Renewable Energy Lab. (NREL), Golden, CO (United States) (2016).
[60] Brackney L, Parker A. OpenStudio Conversion of DEER Prototypes 2018.
[61] Kromer S. Status of Energy Modeling and Data Resources in California Energy Efficiency Programs 2019. https://psdconsulting.com/oep-documents/OEP-California-Stategy.pdf (accessed August 10, 2021).
[62] California Energy Commission. 2019 Building Energy Efficiency Standards for Residential and Nonresidential Buildings - Title 24. 2019.
[63] , Google. Google Maps (2018).
[64] B.J. OpenStreetMap, Packt Publishing Ltd (2010).
[65] H. Butler, M. Daly, A. Doyle, S. Gillies, T. Schaub, E. Wilde, et al., The GeoJSON Format, Electron URL Http//Geojson Org (2014).
[66] Real Estate, Homes for Sale, MLS Listings, Agents | Redfin 2004. https://www.redfin.com/ (accessed July 8, 2021).
[67] United States Census Bureau. American Community Survey 2015. https://www.census.gov/programs-surveys/acs/ (accessed January 1, 2018).
[68] Wilson E. Commercial and Residential Hourly Load Profiles for all TMY3 Locations in the United States - Datasets - OpenEI DOE Open Data 2009. https://openei.org/doe-opendata/dataset/commercial-and-residential-hourly-load-profiles-for-all-tmy3-locations-in-the-united-states (accessed March 20, 2020).
[69] Southern California Edison. Southern California Edison DRPEP 2019. https://drpep.sce.com/drpep/ (accessed February 9, 2022).
[70] Sontag M, Conlon B, Price S, Mantegna G, Horii B, Garnett O, et al. Time Dependent Valuation of Energy for Developing Building Efficiency Standards. 2020.
[71] Big Ladder Software. Elements | Big Ladder Software 2016. https://bigladdersoftware.com/projects/elements/ (accessed February 16, 2022).
[72] N. Aiko, B. Bruno, L. Norford, F.R. Christoph, Urban Heat Island Effect within Urban Design Process (2015).
[73] 2019 Energy Code-Residential Lighting California Energy Commission 2019.
[74] Pacific Gas & Electric. The Pacific Energy Center's Guide to: California Climate Zones and Bioclimatic Design. 2006.