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Electrifying High-Efficiency Future Communities: Impact on Energy, Emissions, and Grid

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A B S T R A C T

To combat climate change and meet decarbonization goals, the building sector is improving energy efficiency and electrifying end uses to reduce carbon emissions from fossil fuels. All-electric buildings are becoming a trend among new constructions, introducing opportunities for decarbonization but also technical challenges and research gaps. For instance, further investigation is needed to understand how the adoption of energy efficiency measures (EEMs) and distributed energy resources (DERs) in all-electric communities would affect energy consumption, carbon emissions, and grid planning. This paper presents a case study of a mixed-use, all-electric community located in Denver, Colorado. We use URBANopt^{TM}, a physics-based urban energy modeling platform to model the community and then evaluate the impact of EEMs and DERs (i.e., photovoltaics [PV], electric vehicles [EVs], and batteries) on the community's energy usage, carbon emissions, and peak demand. The results show that adding EEMs and PV led to both energy consumption and carbon emissions reductions across all building types. However, we saw fairly limited impact of EEMs and PV on buildings' peak demand in our case. Additionally, due to overnight EV charging activities and higher grid carbon intensity at night, the carbon emissions in multifamily buildings have a noticeable increase compared to scenarios without vehicles. Finally, the addition of batteries helped reduce peak demand by 11%–29%. The modeling workflow and evaluation methods can be applied to similar communities to evaluate their performance and the effect of integrating EEMs and DERs.

1. Introduction

In recent years, there has been a growing interest in electrification of energy use for new construction buildings all over the world. Some state and municipal governments in the United States are beginning to enforce the use of all-electric building equipment by updating building codes. For example, Denver's Net Zero Energy New Buildings and Homes Implementation Plan [1] suggests that by 2027, all newly-built commercial and multifamily buildings in the Denver area should be all-electric. The plan sets a similar target for residential homes by 2024. In Europe, the European Union is seeking structural changes to the power sector through end-use electrification and power generation decarbonization to achieve its carbon neutral goal by 2050 [2].

Electrification of buildings can offer both environmental benefits and increased building energy efficiency. Because in cold climates, the majority of building carbon emissions result from space heating and water heating [1], all-electric buildings replace existing fossil fuel demand with electricity demand. This allows the potential for leveraging the increasing penetration of clean energy in the power grid, especially when the increased load temporally matches the renewable generation. From an energy efficiency perspective, heat pumps have an efficiency that is two to three times higher than that of gas equipment [1], which results in energy consumption savings. Lastly, buildings with electric vehicle (EV) chargers facilitate a better coordination between the building and transportation sectors, where rapid electrification is also taking place.

Existing literature focuses on the energy and grid impact of buildings and communities. Gerke et al. [3] analyzed the interactions between energy efficiency and demand response on regional grid scales using a bottom-up energy simulation method. They identified a competitive relationship between efficiency and demand response in many cases, while pointing out that a complementary relationship between the two is also possible, especially with control-based efficiency. Munankarmi et al. [4] studied the relationship between energy efficiency measures (EEMs) and demand flexibility in an all-electric community. They concluded that EEMs together with home energy management systems and battery systems can reduce energy costs while increasing demand flexibility. However, they also found that the potential for flexibility is lower in more energy-efficient homes due to their lower loads. Christensen et al. [5] investigated an all-electric energy system design with geothermal energy resources, EEMs, and photovoltaic (PV) asset dispatch in a cold climate. Their results indicated that geothermal resources are competitive in supporting communities to achieve net zero energy (NZE).

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Table 1
Comparison of relevant studies with the proposed work. This table highlights that among the existing all-electric community works collected in the literature review, only one incorporates large-scale adoption of EVs and batteries. Further, the carbon emissions of future all-electric communities need additional investigation.

Reference	Scope of work			Evaluation perspective		
	Scale	All-electric	EEM & DER	Energy performance	Carbon emissions	Grid impact
[3]	Building, grid	✗	Battery	√	✗	√
[4]	Community	√	EEMs, PV, battery	√	✗	√
[5]	Community	√	EEMs, PV, geotherm, battery	√	✗	✗
[6]	Community	√	PV, battery	√	√	√
[7]	Community	✗	PV	√	✗	√
[8]	Community	✗	EEMs, PV, battery, EV	√	√	√
[9]	Community	√	PV, battery	√	√	√
[10,11]	Building, community	√	PV, battery, heat storage	√	√	√
[12]	Community	√	PV, battery, EV	√	√	✗
[15]	Building	✗	EV	√	✗	√
[16]	Community	✗	PV, EV	√	✗	√
[17]	Community	✗	EV	√	✗	√
Proposed work	Community	√	EEMs, PV, battery, EV	√	√	√

Similarly, Heidi von Korff [6] and Huang et al. [7] focused on the energy performance and grid impact of NZE communities.

A few studies have conducted carbon emission evaluation of buildings and communities in the context of electrification. Jing et al. [8] investigated the role of electrification with flexibility in decarbonization. They demonstrated that electrification is a feasible solution to achieve deep decarbonization, where flexibility provides huge cost-saving potential in end use electrification. Kitagawa et al. [9] quantitatively evaluated the energy performance and annual carbon emissions of a zero-energy residential community in Japan. Their results indicated a positive correlation between energy consumption and annual carbon emissions, where the closer the community is to zero energy, the lower its carbon emissions. Terlouw et al. [10,11] proposed a multi-objective optimization framework to minimize the operation costs and carbon emissions of an all-electric residential energy system. They concluded that community-scale energy storage performs better than home energy storage both economically and environmentally. Wang et al. [12] compared different carbon-emission responsive controllers for residential thermostatically controllable loads in a cold climate. They found that the carbon responsive controllers can reduce the homes' annual carbon emissions by 6.0% to 20.5% with limited impact on thermal comfort and energy costs.

Distributed energy resources (DERs) such as PV panels, battery storage, and EVs play a significant role in shaping community power demand. So far, the impact of integrating PV and battery storage at a community scale has been extensively studied [13,14]. With the electrification of the transportation sector, the impact of EV adoption has gained more attention. Gilleran et al. [15] assessed how station sizes, charging power levels, and utilization factors of EV charging stations affect a big-box retail building's power demand. Their results showed that adding an EV charging station has the potential to increase the building monthly peak demand by over 250%. The annual electricity bill increased by 88% in cold-climate areas paired with utility rate structures that have high demand charges. Ahmad et al. [16] developed an energy management system for public EV charging stations integrated with community microgrids. The objective function aimed at minimizing the cost of EV charging and maximizing the profit from selling the surplus energy from PV and EV systems. Sadati et al. [17] studied the energy management of EV parking lots in a power distribution grid. Optimal scheduling strategies were proposed to help the parking lot owner gain maximal profits under EV uncertainties.

Table 1 compares the existing relevant studies with the proposed work in this paper. Based on the literature review, we identified that there is a lack of studies dedicated to future all-electric communities. Among the existing all-electric community works collected in the literature review, only one incorporates large-scale adoption of EVs and batteries. Further, the carbon emissions of future all-electric communities need additional investigation. To fill these identified gaps, we first modeled a mixed-use, all-electric community located in Denver, Colorado, United States that corresponds to the 2020 local building energy efficiency codes as a baseline. All building loads, except for the natural gas cooking loads in food service buildings, are fueled by electricity. In addition to the baseline scenario, we designed future scenarios that achieve NZE through EEMs and PV systems. In some scenarios, we also considered EV and battery integration. The resulting energy usage, peak demand, and carbon emissions of various scenarios are compared to evaluate the impact of EEMs and DERs in future all-electric communities. The major contributions of this work are summarized as follows:

- Streamlined workflow for modeling large, mixed-use communities using the URBANopt^{TM} platform;
- In-depth impact analysis of EEM and DER adoption in a future all-electric community;
- Quantitative evaluation of energy, carbon emissions, and grid-related performance metrics of the community.

The remainder of this paper is organized as follows: Section 2 describes the community modeling workflow using URBANopt. The selected EEMs and the DERs are also introduced. Section 3 describes the design of the case study containing the community information, the simulation scenarios, and the impact evaluation metrics. Section 4 discusses the simulation results quantitatively. Section 5 concludes the work and recommends topics for further study.

2. Methodology

Simulating energy consumption and distributed generation at a district scale entails modeling different energy components and systems and analyzing their interactions, which is a crucial task for our study. Many tools have been developed to model each of these district components separately, such as EnergyPlus^{TM} for building energy modeling and REopt^{TM} for PV and battery system modeling. However, running energy modeling subtasks interactively through a holistic approach, instead of a standalone modeling process, is needed to identify key opportunities and benefits of energy-efficient technologies. This approach also facilitates a feedback loop between the different components of a district, enhancing the design and operation decision-making for buildings, DERs, and the grid. Therefore, in this study, we utilized URBANopt, a flexible platform that combines multiple modeling tools, to achieve a holistic energy analysis of our district through parallel modeling of the buildings and DER systems.

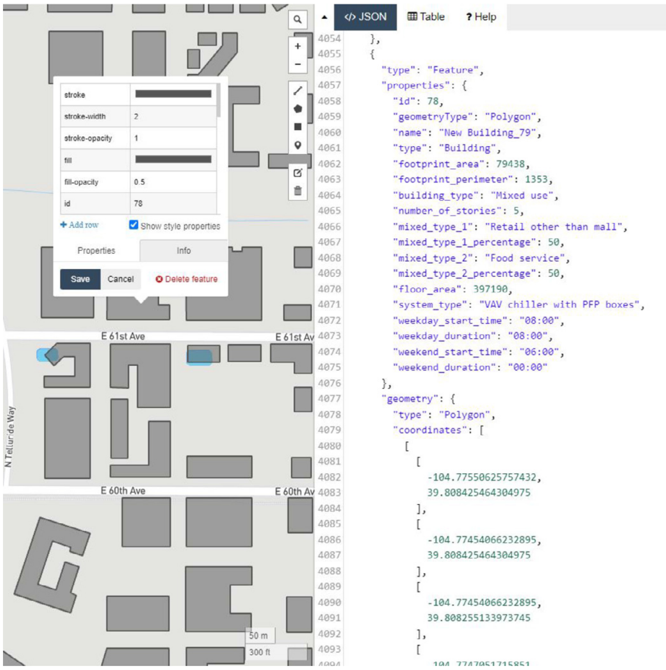

Fig. 1. GeoJSON file combining geospatial and other general building information (visualized on geojson.io).

2.1. Community modeling using URBANopt

URBANopt is an open-source platform to model energy systems in districts. This modular platform integrates multiple tools that enable us to perform district-scale building energy efficiency analysis in conjunction with DER modeling and optimal design within one platform. It facilitates the development of new workflows, which can provide analysis of several energy aspects of a district system and test different scenarios in an integrated modeling approach. The original vision for URBANopt, URBANopt's core modules, and URBANopt's grid-interactive modules are provided in reference [18–20].

In the process of modeling our district, multiple URBANopt modules are utilized to generate different scenarios that combine building and DER models and are characterized with unique EEMs. First, an URBANopt-GeoJSON module organizes geospatial information for the district in a GeoJSON format. Figure 1 shows a sample of the developed GeoJSON file visualized on geojson.io for our district. Then the URBANopt-Scenario module is used to create customized scenarios for our analysis. This module allows us to create various customized templates of inputs and map them to different buildings in a scenario. These templates of inputs describe the model characteristics of a building or DER system and can include a selected list of EEMs. For this case study, we developed three scenario templates characterized with different EEMs: a) a baseline scenario template that is modeled to meet the Denver energy requirements for 2020 [1]; b) a high-efficiency scenario template that applies additional EEMs to meet 2030 Denver building energy goals; c) an EV scenario template that inherits all the characteristics from the high-efficiency scenario and integrates EV charging models. After developing various scenarios, the URBANopt Runner and Post Processor manage the execution of the simulations and aggregate the results for each scenario.

In this process, we also utilized the URBANopt grid-interactive module that integrates REopt, a DER optimization tool [21], to optimally size and dispatch PV and battery systems for each building in the three designed scenario templates. This integrated approach provides a feedback loop between building models and their corresponding DER models. This allows the REopt optimization to optimally size the DER systems based on both building-level and district-level profiles and compute the optimal dispatch of these systems to maximize the system's total life cycle cost savings. The above-described workflow is illustrated in Figure 2.

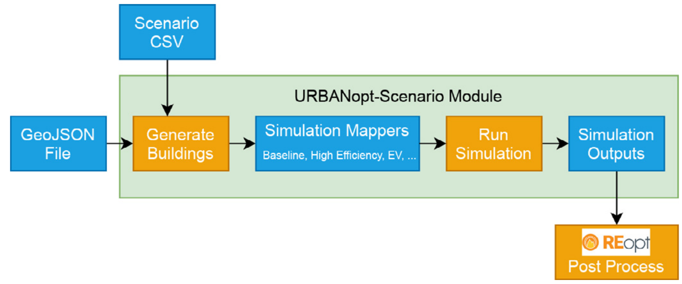

Fig. 2. Diagram of the modeling workflow with URBANopt (figure adapted from [19]). Blue blocks are items and orange blocks are actions.

2.2. Energy efficiency measures

For regions with different climates, the energy savings potential of the same combination of EEMs might vary significantly. According to a sensitivity analysis study in the United States [22] and a dedicated technical report for the area [23], the top EEMs for Denver (climate zone 5B) include increasing electrical equipment efficiency, increasing lighting system efficiency, replacing window material, and adding wall insulation. Table 2 lists the EEMs selected in this work to achieve an energy efficiency upgrade from the baseline scenario to the high-efficiency future scenario. Note that in this work, the heating, ventilation, and air-conditioning (HVAC) systems for all buildings are powered by electricity, so we included efficiency upgrades of this equipment as well. Given that the windows in the baseline scenario is already highly energy-efficient, we did not include window-related EEMs in this case.

2.3. Distributed energy resources

PV panel sizing and dispatching. The PV panels in this work are all assumed to be behind the meter. In the baseline scenario, 75% of each building's rooftop area is assumed to be covered by PV. The following equation estimates the PV system size in kW (direct current) according to the available area [24]:

$$P_{pv} = A \cdot gcr \cdot 1\ kW/m^2 \cdot \eta, \tag{1}$$

where P_{pv} is the rooftop PV system size in kW, A is the available rooftop area in m^2, gcr is the ground cover ratio which is assumed to be 0.4, η is the PV system module efficiency which is assumed to be 19%. To maximize the utilization of the local solar energy resources, we ran a solar radiation analysis covering all the possible combinations of PV panel tilt angles and azimuths for Denver. The tilt and azimuth that yielded the highest year-round solar radiation value were then identified, where the optimal tilt was identified to be 36° and azimuth to be 171°. It is assumed in this work that all the buildings in the studied community have flat roofs.

In scenarios where building-level NZE is achieved, ground PV panels are added to offset the deviation between the annual PV generation and energy consumption. The following equation estimates the ground PV panel area to achieve annual NZE at the building level:

$$P'_{pv} = P_{pv}\,\left(\frac{E_{con.}}{E_{pv}} - 1\right) \tag{2}$$

In Equation 2, P'_{pv} represents the extra ground PV system size. The $E_{con.}$ and E_{pv} are the annual building electricity consumption and PV energy generated by the rooftop PV system, respectively. The gcr and the efficiency η of both rooftop and ground PV panels are assumed to be the same. We note that because of the limited land space in the community

Table 2
Selected measures for increasing energy efficiency in residential and commercial buildings implemented in this work.

	Residential	Commercial
1	Increase heat pump heating efficiency	Increase heating equipment efficiency
2	Increase heat pump cooling efficiency	Increase cooling equipment efficiency
3	Increase wall R-value	Increase exterior wall insulation R-value
4	Increase lighting efficiency	Increase lighting efficiency
5	Decrease plug load usage	Reduce miscellaneous equipment power
6	Decrease water usage	N/A

for placing all ground PV panels, we assume the ground PV panels are installed in an open space offsite.

EV charging load. The EV charging load in this work is modeled as static load profiles added on top of the other building loads. The load profiles were created for a Denver district to reflect different potential EV charging behavior [25]. Three charging station types were differentiated while generating the profiles: residential, public, and workplace. The URBANopt building types are mapped to these three building types. The "business as usual" charging behavior was chosen, which represents home dominant charging behavior, where the majority of the EV charging happens during evening hours and overnight. Minimum charging power mode was selected to avoid a significant increase in peak demand during the charging events. The EV penetration rate was assumed to be 100%, meaning all vehicles on site are electric. More information about the EV modeling can be found in the documentation [26].

Battery sizing and dispatching. The sizing and dispatching of the batteries in this work was conducted using REopt [21] with an optimization-based approach. The mixed-integer linear program takes in inputs such as analysis goals, economic assumptions, policy-based incentives, utility rates, technology assumptions, and building loads and then optimizes system sizing and controls for the maximum value [27]. For instance, in the financial analysis option, REopt finds the optimal battery size and dispatch decisions that minimize the life cycle cost of energy, considering not only operational but also installation and replacement costs of batteries. Technical constraints of batteries such as the minimum state of charge, round-trip efficiency, and charge/discharge rate limits are considered. Important control assumptions about whether the battery can be charged with grid power are determined by the user through assumption files. More descriptions of REopt and its applications can be found in the reference [28–30].

3. Case study

This section specifies the design of the case study to demonstrate the proposed workflow. First, we describe the mixed-use community in detail. Then, we present the design of the simulation scenarios in this study. Last, we discuss the selected metrics for quantifying the impact of EEMs and DERs on the all-electric community's energy and emissions.

3.1. Community information

The community used in the case study is located in Denver, Colorado, United States, which has a cold and dry climate according to ASHRAE Standard 169-2006 [31]. The community is currently under construction and going to have 148 buildings, most of which are large commercial buildings such as office buildings and retail stores. All residential buildings in this community are multifamily buildings. Figure 3 shows a three-dimensional rendering map of the community with color-coded building types. A list of detailed building types can also be found in Table 3. In the office with retail buildings, the mixed ratio by floor area is assumed to be 90% office with 10% retail. In the retail with food service buildings, the ratio is 50% and 50%.

The building loads are all electric. More specifically, the HVAC system types include air-source heat pumps for residential buildings. Packaged rooftop heat pumps, packaged variable air volume (VAV) with parallel fan powered (PFP) boxes, or VAV chiller with PFP boxes are used for commercial buildings depending on the building floor area and number of floors [32]. The domestic hot water systems are also powered by electricity. However, in food service buildings (i.e., restaurants), there is some remaining natural gas usage due to the natural gas-fueled cooking equipment. This aligns with Denver's NZE implementation plan [1] and is thus not included in the calculations of NZE.

Fig. 3. Three-dimensional rendering map of the mixed-use case study community. The community is currently under construction and going to have 148 buildings, most of which are large commercial buildings. It is located in Denver, Colorado, United States.

Table 3
Building types in the mixed-use community. Ten building types can be differentiated. All residential buildings are multifamily buildings.

Building type		Quantity
Mixed	Office with retail	15
use	Retail with food service	19
Multifamily		36
Food service		16
Strip shopping mall		14
Office		23
Retail other than mall		12
Lodging		4
Education		3
Outpatient health care		6
Total		148

Local utility rates from Xcel Energy were adopted to evaluate the annual energy costs and inform the optimal battery dispatching. Table 4 shows the adopted residential and commercial utility rates [33,34]. In the table, the renewable energy credit (REC) payment stands for the credits the customers will obtain for every kWh of renewable energy generation. The excess PV payment represents the profit gained from the surplus amount of PV that is sold back to the grid.

3.2. Scenario design

Figure 4 depicts the five scenarios designed for the case study. The baseline scenario simulates the community with a year 2020 energy efficiency level. The ASHRAE 90.1-2019 prototypical building models were

Table 4
Local residential and commercial utility rates. Both rates consists of fixed charge, energy charge, and demand charge. Energy net-metering is enabled. The REC payment stands for the credits the customers will obtain for every kWh of renewable energy generation. The excess PV payment represents the profit gained from the surplus amount of PV sold back to the grid.

Item	Residential rate	Commercial rate
Fixed charge ($/month)	5.58	39.3
Energy charge ($/kWh)	0.03035 (off-peak); 0.04631 (on-peak)	0.040246
Demand charge ($/kW)	12.33 (Oct.–May); 15.54 (Jun.–Sep.)	18.45 (Oct.–May); 22.47 (Jun.–Sep.)
Net-metering	Yes	Yes
REC payment ($/kWh)	0.005	
Excess PV payment ($/kWh)	0.011	

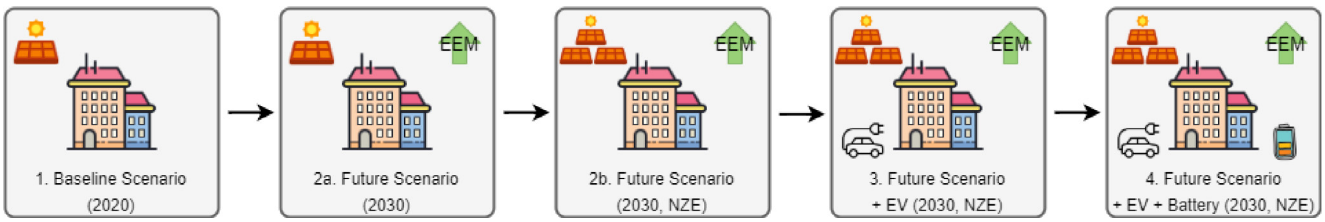

Fig. 4. Scenarios designed for the case study. The future scenario builds upon the baseline scenario with a higher energy efficiency level in alignment with future projected building code requirements.

adapted with some efficiency upgrades to reflect the requirements of local building codes. In the future scenario (2a), the EEMs discussed in Section 2.2 were applied to achieve the energy efficiency levels projected for Denver's new buildings in 2030 [1]. In both aforementioned scenarios, the PV panels take up 75% of each building's rooftop area. In the future NZE scenario (2b), ground PV panels were sized (refer to Section 2.3) and added to help achieve building-level NZE. Next, Scenarios 3 and 4 build upon Scenario 2b by incorporating EVs and batteries, respectively.

The design of simulation scenarios enables a sequential variation between adjacent scenarios, which facilitates the impact study of the adoption of certain building energy assets. For instance, through the comparison of the simulation results of Scenarios 1 and 2a, we are able to investigate the impact of the selected EEMs on building performance in an all-electric community. Similarly, the impact of large-scale EV and battery adoption in all-electric communities can be studied through comparing Scenarios 2b, 3, and 4, sequentially. Note that the modeling and calculation of internal combustion engine vehicle emissions are out of this paper's scope. Hence, in Scenarios 1, 2a, and 2b, no vehicles are modeled. The selected building performance evaluation metrics in this paper will be introduced in the following subsection.

3.3. Evaluation metrics

The building energy usage in this work is quantified by the net electricity usage intensity (denoted as EUI in this paper) and the annual energy cost. The net EUI can be defined with the following equation:

$$EUI_{net} = \frac{\sum_{t=1}^{N} (P^t_{grid} - P^t_{pv})\,\Delta t}{A_{floor}}, \tag{3}$$

where N is the total number of simulation time steps in a year, P^t_{grid} is the average electric power draw from the grid at each time step t, P^t_{pv} is the PV generation at each time step, Δt is the time step interval (one hour), and A_{floor} is the building floor area. The grid impact of the community is evaluated with the monthly peak demand as power distribution system planning is mainly dependent on the regional peak demand. One aspect of the environmental impact of the community can be quantified with the annual operational carbon emissions, which indicates the emissions associated with the generation of grid power.

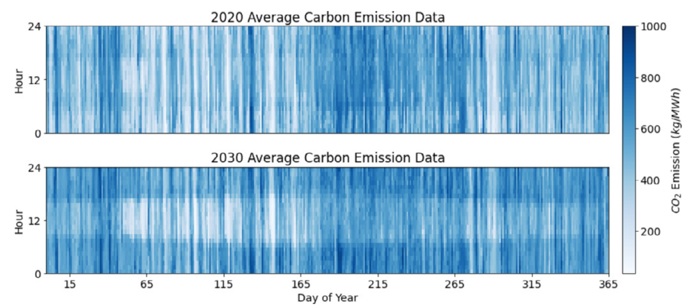

Fig. 5. Projected average carbon emission intensity of the grid power generation for Denver area from Cambium (as of October 2020). There is a slight decrease of carbon intensities in year 2030 compared to 2020, especially during the spring. There also exists a more explicit daily variation of carbon intensities in 2030 due to the higher PV generation power during the day.

The following equation calculates the annual total operational carbon emissions of each building:

$$C = \sum_{t=1}^{N} e^t_{CO_2}\, P^t_{grid}\, \Delta t, \tag{4}$$

where $e^t_{CO_2}$ represents the average carbon dioxide (CO_2) intensity of the grid power generation mix at each time step. Note that carbon net-metering is not considered in the calculation, meaning that the PV energy exported back to the grid brings in only excess PV payment but no carbon emissions offsetting benefits. In this work, the carbon intensity data of the grid is adopted from the Cambium data set [35]. Based on modeled futures of the U.S. electricity sector, Cambium assembles structured data sets of energy-related metrics (e.g., carbon emissions) to facilitate long-term decision-making. Specifically, the hourly average carbon emission data from the Standard Scenarios 2020 Mid-case scenario for Denver's local balancing authority were adopted. Though Cambium provides various scenario settings such as high versus low renewable energy cost, we note that the simulated data are based on certain assumptions about the future projected U.S. electric sector. These assumptions are subject to many uncertainties, such as climate change and policy impacts, which could affect the analysis of this work.

Figure 5 visualizes the average carbon emissions data for the selected simulation years from Cambium (as of October 2020). From the figure, we see a slight decrease of carbon intensities in year 2030 compared

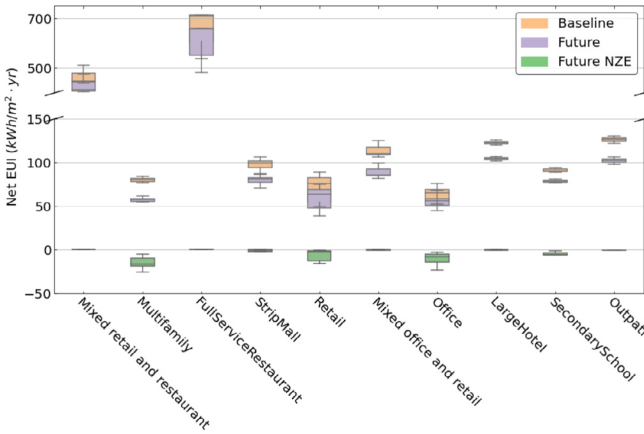

Fig. 6. Net EUI by building type (Scenarios 1, 2a, and 2b). There exist some reductions of electricity usage from the baseline to the future scenario because of the adoption of EEMs. For the future NZE scenario, in every building type, the annual net EUI is around zero.

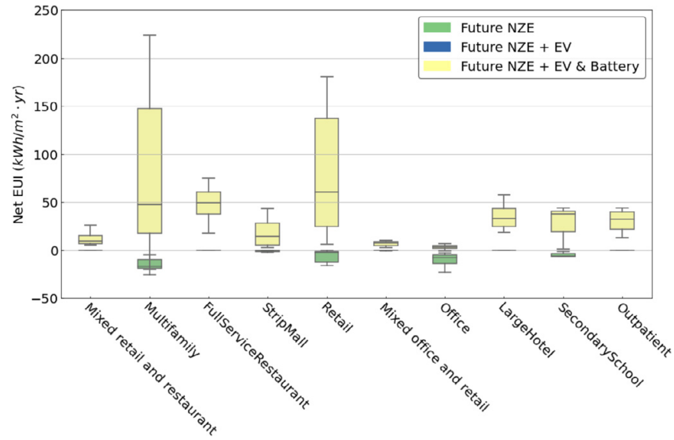

Fig. 7. Net EUI by building type (Scenarios 2b, 3, and 4). In the figure, the boxes for the EV scenario overlap with those of the EV & battery scenario. Adding EV loads to the buildings not only increases the building mean EUI values but also enlarges the range of EUIs, especially in multifamily and retail buildings.

to 2020, especially during the spring. We also see a more explicit daily variation of carbon intensities in 2030 due to the higher PV generation power during the day. Given the U.S. government's aggressive emission reduction goals [36], more clean hours than plotted in this figure should be seen by 2030 due to the integration of more clean power generation technologies.

4. Results and discussions

4.1. Net EUI

Figure 6 compares the net EUI values by building type across the baseline, future, and future NZE scenarios. From the figure, we see some reductions of electricity usage from the baseline to the future scenario because of the adoption of EEMs. The largest relative reduction was within multifamily buildings (28%), and the smallest was in the mixed retail and restaurant building (7.5%). According to Denver's NZE implementation plan for new buildings and homes [1], the EUI values for 2030 are projected to be 170 $kWh/m^2 \cdot yr$ for large hotels, 117 for large offices, 88 for standalone retailers, and 73 for mid-rise apartment buildings. Therefore, the net EUI values in the future scenario generally correspond to those projected in Denver's plan.

Looking at the future NZE scenario, where extra ground PV panels were added to help achieve building NZE, we see that in every building type, the annual net EUI is around zero. The multifamily buildings have the smallest net EUI values, at around -19 $kWh/m^2 \cdot yr$. This indicates that the annual electricity consumption of the community can be balanced out by behind-the-meter PV generation. The community also makes profits from selling the surplus generation of renewable energy back to the grid, which will be discussed in Section 4.4.

Figure 7 compares the net EUI values by building type across future NZE, EV, and EV & battery scenarios. In the figure, the boxes for the EV scenario overlap with those of the EV & battery scenario. This is because batteries work as temporal arbitrage here and did not affect the total building energy consumption too much, where a charging and discharging efficiency of 0.94 was assumed. We notice from the figure that adding EV loads to the buildings not only increases the building mean EUI values but also enlarges the range of EUIs, especially in multifamily and retail buildings. This can be attributed to the fact that the building EV profiles modeled in this work are only correlated with factors such as the building type and charging behavior, but are independent of the floor area. Hence, the same EV loads were added to each building of the same type, despite varying floor areas across individual buildings. This has led to much-scattered distributions of net EUI values. In our case study community, the multifamily and retail buildings have relatively smaller floor areas. This caused their maximum net EUI values to be larger than other building types.

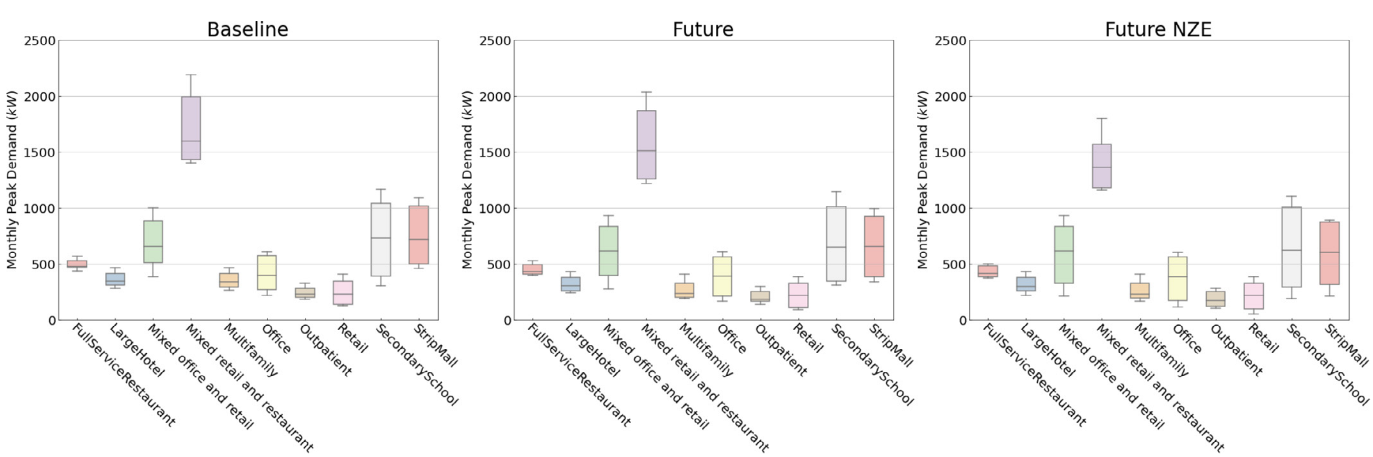

Fig. 8. Monthly peak demand by building type (Scenarios 1, 2a, and 2b). The adoption of EEMs has limited impact on the buildings' peak demand. However, adding ground PV panels in the future NZE scenario further reduces peak demand.

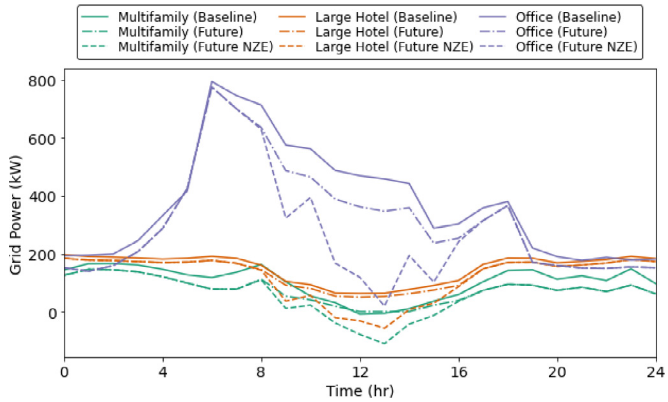

Fig. 9. Building power demand curves for selected buildings on a winter day (January 1, Scenarios 1, 2a, and 2b). The figure shows uniform load reductions throughout the day comparing the baseline and the future scenario. In future NZE scenario, peak PV power generation occurs mainly around noon or early afternoon, which does not align with the building peak load hours.

4.2. Peak demand

The boxplot of the monthly peak demand by building type for the baseline, future, and future NZE scenarios can be found in Figure 8. From the figure, we notice that the adoption of EEMs has limited impact on the buildings' peak demand. This is likely attributable to the fact that our chosen baseline is already highly energy efficient. Adding ground PV panels in the future NZE scenario further reduces peak demand. However, the peak demand reduction effect is much less than its net EUI reduction effect as shown in Figure 6. Comparing the future NZE and baseline scenarios, the largest peak demand reduction lies in the multifamily buildings (26.3%), and the smallest in office buildings (11.4%).

Figure 9 plots sample curves of the grid power draw of selected building types on a winter day. The figure further explains the reason for the limited peak demand-shaving impact of the adopted EEMs. From the figure, we generally see uniform load reductions throughout the day when comparing the baseline and the future scenario. However, such uniform reduction trends have fairly limited impact on the building peak load, which occurs in the early morning around 7 a.m. when people get up or arrive at the workplace and the building energy systems start to operate. Likewise, peak PV power generation occurs mainly around noon or early afternoon, which also does not align with the building peak load hours. We note that no building load control has been considered as an EEM in this paper, which could have limited the peak shaving effect. The grid power draw of the rest building types can be found in Figure A.2.

Next, the impact of adding behind-the-meter EV loads and batteries on building peak demand is shown in Figure 10. Adding EV loads to the buildings increased the average monthly peak demand by 15–110 kW, depending on the building type. Furthermore, adding batteries has reduced building peak demand by around 20% due to load shifting effects. A demand curve plot for all the building types comparing Scenarios 2b, 3, and 4 can be found in Appendix A.

Table 5
Average monthly peak demand values in the future NZE scenario in kW and relative changes in percentage in future NZE with EV and future NZE with EV and battery by building type.

Building type	Future NZE	EV	EV & battery
Full service restaurant	428	6%	-14%
Large hotel	317	34%	-11%
Mixed office and retail	585	3%	-22%
Mixed retail and restaurant	1397	2%	-15%
Multifamily	258	43%	-15%
Office	362	6%	-29%
Outpatient	182	16%	-26%
Retail	219	8%	-22%
Secondary school	637	4%	-21%
Strip mall	590	3%	-25%

Table 5 lists the detailed average monthly peak demand values and relative changes by building type to provide more insights. We note that the relative peak demand changes of the EV scenario are calculated relative to the future NZE scenario, and those of the EV & battery scenario are calculated relative to the EV scenario. From the table, the largest and smallest peak demand changes occurred with the multifamily building (43%) and the mixed retail and restaurant building (2%), respectively. Given the EV load profiles of the two building types are of a similar scale, the differences in the relative changes are mainly caused by the deviations of the original building loads. Further, the addition of batteries helped reduce the peak demands by 11%–29%. This exceptional peak demand reduction effect can be partially attributed to the peak demand charges in the utility rates, which will be discussed in detail in Section 4.4.

4.3. Carbon emissions

Figure 11 depicts the annual total carbon emissions by building type. We generally see very similar trends across different scenarios and building types. For instance, a reduction of 7%–24% is seen from the baseline

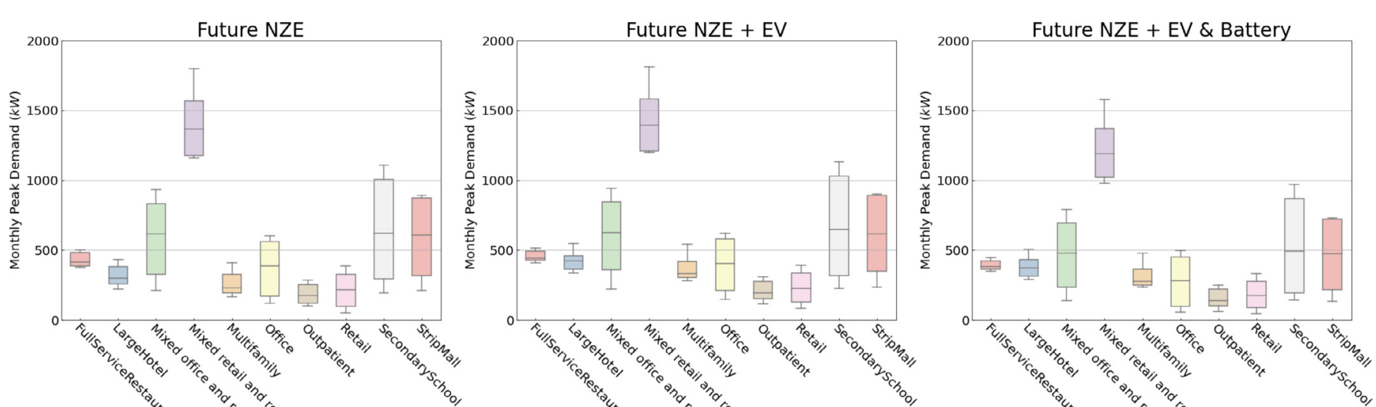

Fig. 10. Monthly peak demand by building type (Scenarios 2b, 3, and 4). Adding EV loads to the buildings increased the average monthly peak demand by 15–110 kW. Adding batteries has reduced building peak demand by around 20% due to load shifting effects.

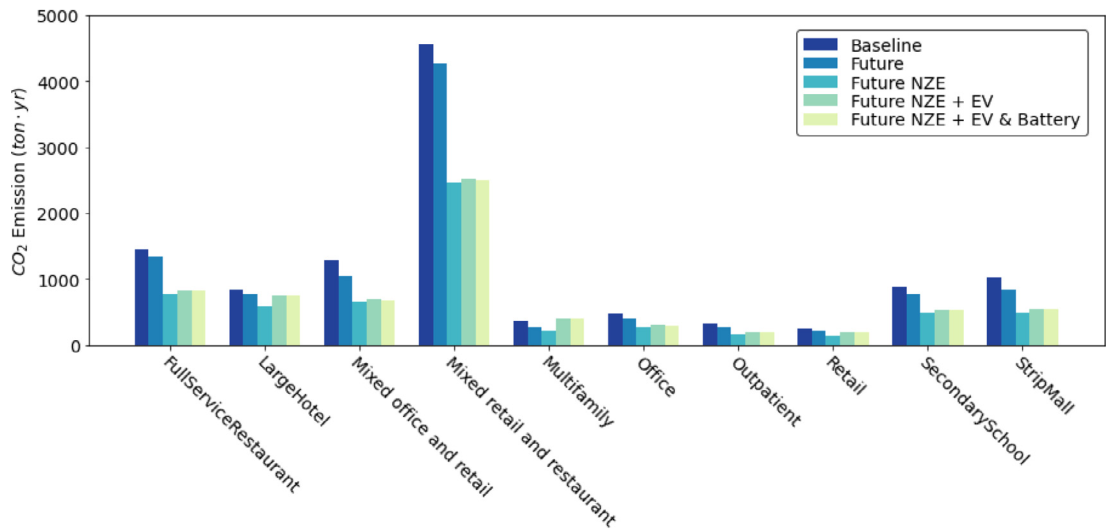

Fig. 11. Mean annual carbon emissions by building type. A reduction of 7%–24% is seen from the baseline to the future scenario due to the adoption of EEMs. There exists a larger reduction of 19%–42% from the future scenario to the future NZE scenario. Adding EV has led to an increase in emissions compared to scenarios without internal combustion engine vehicles.

to the future scenario due to the adoption of EEMs. Then, there exists a larger reduction of 19%–42% from the future scenario to the future NZE scenario. This is attributable to the extra ground PV panels, which reduce the community's dependence on the power grid for electricity during the day. Compared to emission-free clean PV power generation, the grid power generation mix in the United States is dominated by natural gas fired power plants, which have higher carbon intensities. Finally, adding EV loads introduces a minor rise of emissions (except in multifamily buildings) that is later mitigated to some extent by the batteries.

Among all the building types, the carbon emissions of multifamily buildings showcase a different trend across the scenarios. Based on the barplot, the emissions after introducing EV loads even exceed those of the baseline scenario[1]. Given that the total energy usage of the EV scenario did not exceed the baseline (see Figures 6 and 7), this can be attributed to the fact that EV charging in multifamily buildings typically happens overnight, as illustrated by Figure 12, when there is no PV power and the carbon emission intensity of the grid power is relatively high (see Figure 5). Though adding batteries can shift the clean energy from the daytime to the nighttime, in our case, the influence has been limited because other household loads also occur at night.

4.4. Energy costs

The energy costs considered in this work consist of the fixed charge, energy charge, demand charge, and credits obtained from renewable energy generation. Figure 13 plots the energy and demand charge, as well as the renewable (i.e., PV) credits by building type across different scenarios. In the figure, the PV credits incorporate both the REC payment and the excess PV payment as indicated in Table 4. In all building types, the demand charge constitutes a larger portion of the total cost than the energy charge. Across various scenarios, the energy charge reduction seen in the future NZE scenario as compared to the future scenario is much more prominent than the corresponding reduction in the demand charges. This is consistent with the limited peak demand shaving effect of extra PV panels discussed in Section 4.2. Further, though annual NZE was achieved and total PV generation offsets total energy consumption for each building, the PV credits obtained cannot cancel out the energy charge under the current local utility rate structure.

More specifically, to analyze the cost savings of the extra ground PV panels, we compare the future NZE scenario with the future scenario. 19.5%–40.0% of total energy costs were reduced, among which about 46% was attributed to the energy charge reduction, 16% to the demand charge, and 38% to the PV credits. However, it is worth noting that the land space required to host the extra ground PV panels, as well as their capital and maintenance costs, play an important role in the economic analysis of such renewable investments. This work focuses on the operational cost analysis and thus has not included the upfront capital costs in the analysis of the EEMs and DERs.

Moreover, the operational energy cost saving effect of batteries can be illustrated through comparing the EV and EV & battery scenarios. The total utility bill cost savings from the installation of the batteries lies between 8.1%–27.2%. The largest cost savings comes from the reduction in demand charge, which accounts for about 98% of the total savings from batteries. Almost no change of PV credits was seen between the two scenarios as the REopt optimization determined to export all the surplus PV generation and use the grid power to charge the batteries.

4.5. Community aggregated performance

This subsection discusses the community aggregated performance and the contribution of each building type regarding the annual energy consumption, annual carbon emissions, and demand curve. Figure 14 compares the community annual energy consumption by building type in the baseline scenario (Scenario 1) and the future NZE scenario with EVs and batteries (Scenario 4). In the baseline scenario, the largest energy-consuming type is the mixed retail and restaurant building. However, in the future scenario, the multifamily building becomes the top energy consumer. This is because, with the help of the rooftop and ground PV panels, all buildings achieved annual NZE in Scenario 2b by feeding surplus PV generation back to the grid. After adding the EV charging loads in Scenarios 3 and 4, the surplus PV generation in multifamily buildings cannot offset the large EV charging loads, while other buildings still can. This has significantly increased the net energy consumption of the multifamily buildings.

[1] The baseline scenario and scenarios 2a, 2b do not model any internal combustion engine vehicle emissions. If those were modeled, the trend shown in this plot should be different.

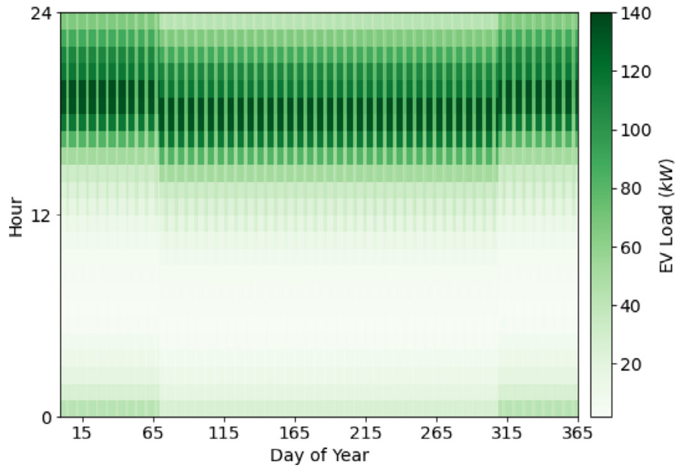

Fig. 12. Heat map of the annual EV charging load for a selected multifamily building. The figure shows that EV charging in multifamily buildings typically happens overnight.

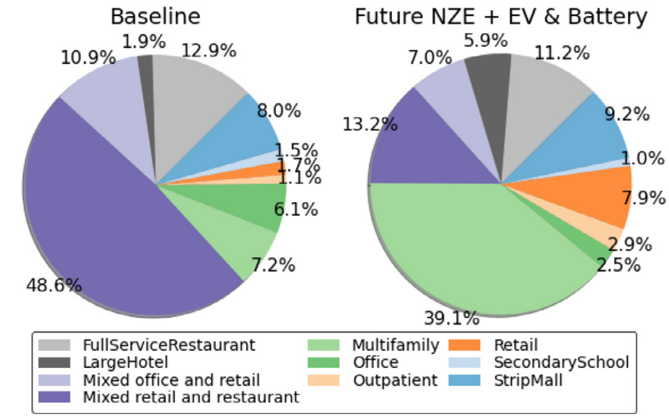

Fig. 14. Community annual net energy consumption by building type. In the baseline scenario, the largest energy-consuming type is the mixed retail and restaurant building. However, in the future scenario, the multifamily building becomes the top energy consumer.

Figure 15 plots the community annual carbon emissions by building type. Unlike the annual net energy, we see a similar distribution of emissions in the baseline scenario and the future NZE scenario with EVs and batteries. This can be attributed to the fact that carbon net-metering was not considered in the calculation of annual carbon emissions. Therefore, for the buildings that are back-feeding to the grid, the exported clean energy cannot offset the emissions caused by the building loads. Regarding the multifamily building, which is the largest energy consumer, they are not impacted by the net-metering scheme because they are not exporting as much PV energy as the other building types. This implies that for future NZE communities, enabling carbon net-metering will further reward energy prosumers, especially when large EV loads or carbon price is present.

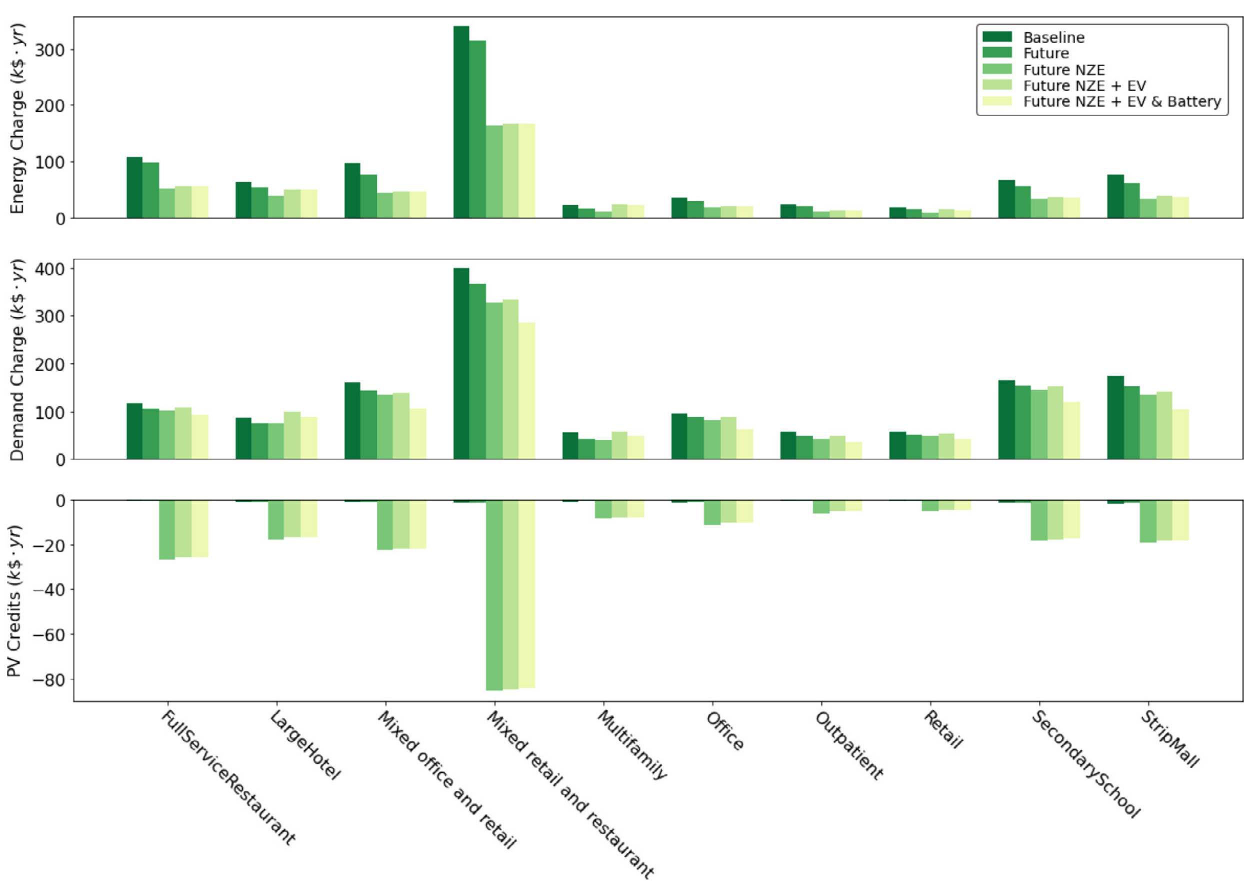

Fig. 13. Mean annual operational energy costs by building type. In all building types, the demand charge constitutes a larger portion of the total cost than the energy charge. The negative values represent the obtained renewable credits.

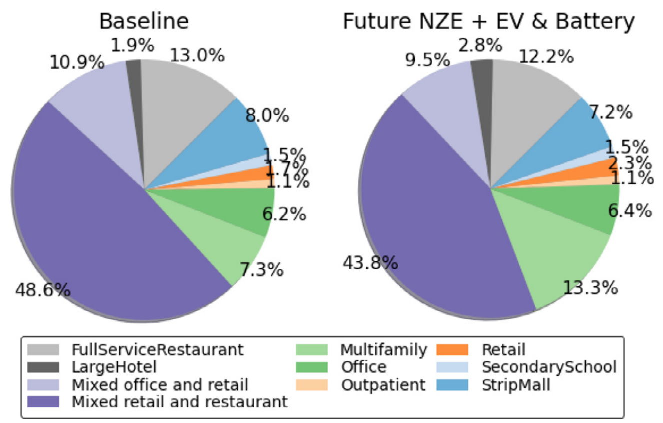

Fig. 15. Community annual carbon emissions by building type. There is a similar distribution of emissions in the baseline scenario and the future NZE scenario with EVs and batteries.

5. Conclusion

In this work, we demonstrated a streamlined workflow for modeling large mixed-use, all-electric communities. A community located in Denver with 148 buildings was modeled and simulated in five scenarios using the workflow. Through the case study, we discussed the impact of adopting EEMs and DERs (i.e., PV, EV, battery) in a future all-electric community. Meanwhile, a comprehensive evaluation of the energy, carbon emissions, and peak demand was conducted. The proposed workflow and findings can be applied to general mixed-use, all-electric communities to inform their design, retrofit, and analysis.

Based on the simulation results, we found that adding EEMs tends to cause fairly uniform reductions in the building loads throughout the day, while adding PV panels mainly reduces the loads around noon. Both of the aforementioned factors lead to fairly limited impact on the building peak load. Additionally, although the annual building-level NZE goal was achieved in one scenario, the total PV credits obtained from local generation cannot fully offset the energy charge under the current local utility rate structure.

In terms of the impact of large-scale adoption of DERs, adding EV loads would greatly impact building EUIs, especially those with smaller floor areas. Further, the carbon emissions in multifamily buildings had a noticeable increase due to the overnight EV loads. The addition of batteries helped reduce peak demand by 11%–29%. This peak demand reduction effect contributed significantly to the decrease in total energy costs, as the demand charge is proportionally larger than the energy charge under the current utility rates. Finally, for future NZE communities, enabling carbon net-metering will help further reward energy prosumers, especially when large EV loads or carbon price is present.

This work has the limitation of modeling the EV loads with static profiles, which are only correlated with factors such as the building type and charging behavior, but are independent of the building floor area or occupancy status. Also, no building load shifting or EV load control was implemented, which could potentially further reduce the peak demand and energy costs by aligning the loads with PV production. Finally, because EnergyPlus prototypical building models of various types were adopted, the same default building schedules were simulated for each type. This could have led to a higher modeled community peak demand than would be expected. Future research directions include:

- Implementation of stochastic building occupancy schedules to mimic more realistic building load shapes.
- Adoption of dynamic modeling of EV loads based on building information and occupancy status.
- Introduction of building and EV load control, as well as thermal energy storage, to enable higher load flexibility and better coordination with PV and the grid.
- Expansion of the research topic to involve PM2.5 emissions of all-electric communities and the resulting regional air quality and health aspects.

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

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Appendix A

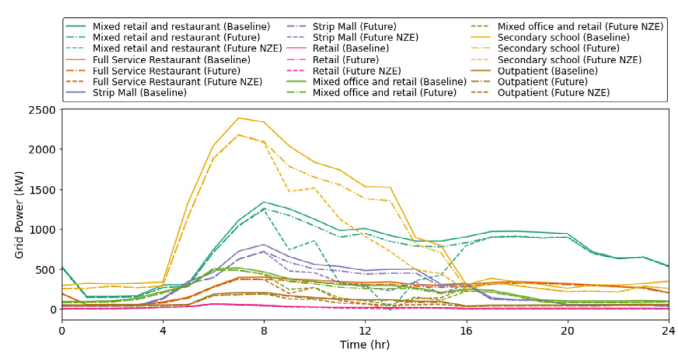

Fig. A.1. Building power demand curves for the rest seven building types on a winter day (January 1, Scenarios 1, 2a, and 2b). This figure complements Figure 9.

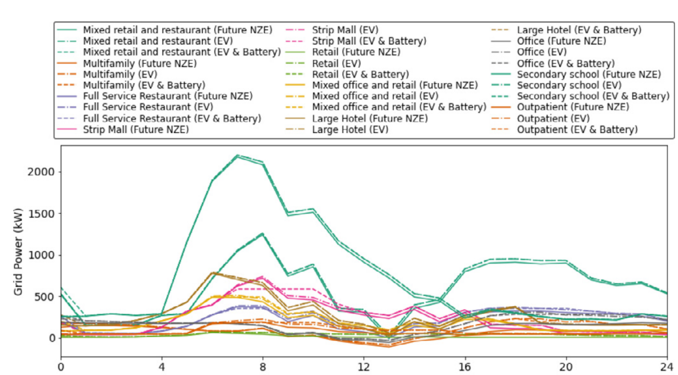

Fig. A.2. Building power demand curves for all the building types on a winter day (January 1, Scenarios 2b, 3, and 4).

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